Journal of Organizational and End User Computing
Volume 35 • Issue 1

High-Quality Growth in Rural China:
Systems-Based Analysis of Digital Entrepreneurial Ecosystems

Xiaotong Liu, Qingdao University, China
https://orcid.org/0000-0003-1141-9184

Chengshuang Qi, Shanghai University of Finance and Economics, China

Yu Liu, Gansu University of Political Science and Law, China

Yuhuan Xia, Shandong University, China*

Haili Wu, University College London, UK
https://orcid.org/0000-0003-1951-1452

ABSTRACT

Research has often overlooked the role of digital innovation in driving social transformation, especially in underserved rural areas, but the integration of digital technology is promoting rural high-quality development through the establishment of digital entrepreneurial ecosystems. Approaching from a complex systems perspective, this study contends that these ecosystems navigate multiple routes to enhance total factor productivity (TFP) in rural settings. Performing a configurational analysis of a sample of 60 demonstration counties for rural revitalization in China, this study identifies three primary pathways yielding high TFP: an investment-led model under government stewardship, a collaborative model steered by both government and social capital, and a talent-centric model governed by digital market forces. Conversely, this study also pinpoints a pathway that does not yield high TFP. Theoretical and practical insights are offered for researchers and practitioners exploring digital innovation and its implications for rural entrepreneurial ecosystems.

KEYWORDS

Digital Entrepreneurial Ecosystems, Digital Technology, Fuzzy-Set Qualitative Comparative Analysis, High-Quality Development, Total Factor Productivity

INTRODUCTION

The widespread use of digital technologies, which are composed of digital components, digital platforms, and digital infrastructure (Nambisan, 2017), accelerated the integration of emerging data factors and traditional production factors and then promoted the restructuring of global economic, institutional, and social systems (Vaio et al., 2021). Digital innovations contribute positively to

DOI: 10.4018/JOEUC.332063 *Corresponding Author

organizational or regional sustainability transitions (George et al., 2021; Tuukka et al., 2023), offering possibilities to promote equality of opportunity, alleviate relative poverty, and achieve common prosperity. People at the bottom of the pyramid (BOP) play multiple roles including producers, consumers, and entrepreneurs (Leong et al., 2016), achieving resource integration, capacity development, and income creation (Fu et al., 2023), Therefore, digital innovation has undeniably contributed to influencing rural development. Existing research has discussed the role of the Internet and e-commerce in increasing rural household incomes (see, e.g., Qiu et al., 2021). Because rural regions are at a disadvantage when it comes to competitive positioning in the digital age, digital innovation remains a niche topic in rural development studies (Roberts et al., 2017). In China, digitization provides a new perspective of high-quality rural development. Its application alleviates information asymmetry and resource constraints thus driving the upgrading of the rural industrial chain, in other words, the reconfiguration of agricultural production factors. One of the core indicators of high-quality rural development is the improvement of total factor productivity (TFP). TFP reflects the overall efficiency of various input factors being converted into output and represents the potential of regional economic growth and high-quality development (Yang et al., 2022; Zheng et al., 2009). How digital innovation contributes to high-quality rural development as measured by TFP deserves further attention.

The concepts of entrepreneurship and innovation have been intertwined with social development since the time of Schumpeter (1912), and digital innovation contributes to high-quality rural development by affecting current rural entrepreneurship. Entrepreneurship is recognized as a means to deal with the challenges of persistent rural poverty in developing countries (Jonas et al., 2021). Its activities require pooling resources, thus entrepreneurial ecosystems are ways to contextualize the increasingly complex and interdependent socioeconomic systems being created (Sussan & Acs, 2017). Scholars argue that developing entrepreneurial ecosystems in a rural context is necessary (Audretsch & Belitski, 2017; Miles & Morrison, 2020) because they are different from urban entrepreneurial ecosystems (Miles & Morrison, 2020).

Rural regions are often characterized by fewer resources such as infrastructure and human capital, less access to funding and government support, and less diversity of economic activity (Bosma & Sternberg, 2014; Dubini, 1989). Market demand in rural economies is systemic rather than exogenous and must be developed, often through market creation initiatives (Darroch & Miles, 2011). Natural capital endowment is more prominent and social embeddedness is more nuanced in rural regions (Emery & Flora, 2006). Digital innovation plays an important role in developing rural entrepreneurial ecosystems, promoting its transformation to digitization. Digital innovation changes the process of rural digital entrepreneurial opportunity identification and commercialization, improves the efficiency of resource allocation, and reduces production costs. For instance, the emergence of Taobao villages[1] in China's rural areas is one phenomenon. Information and communication technology can empower a marginalized community, giving rise to rural e-commerce ecosystems that can aid self-development (Leong et al., 2016). Through digital platforms, rural entrepreneurs can effectually access external sources of financial support, technical guidance, and market knowledge. And digital entrepreneurial ecosystems can minimize the risk-benefit trade-off of rural entrepreneurs, break resource and capability constraints, and increase marginal returns.

We argue that there is an important relationship between digital entrepreneurial ecosystems and rural development. The specific mechanisms and pathways by which digital entrepreneurial ecosystems affect rural development, however, remain unclear and untested. We analyze the multiple relationships between the digital entrepreneurial ecosystem elements and rural TFP from the perspective of complexity by investigating a sample of 60 demonstration counties for rural revitalization in China. We aim to make the following contributions to the literature. First, whereas digital technologies are global, the development of digital activities remains local, and few scholars have paid attention to regional difference of digital entrepreneurial ecosystems (Sussan & Acs, 2017). Given the uniqueness of rural entrepreneurial ecosystems compared with urban entrepreneurial ecosystems (Miles & Morrison,

2020), we explore important digital entrepreneurial ecosystem elements influencing the Chinese countryside such as digital infrastructure and digital formal and informal institutional environment. Technological drivers, structural transformation, and transaction cost reduction are the mechanisms that affect the action of each element. In contrast to the past literature, our findings show that some of the elements might not always be necessary for promoting rural high-quality development under all configurations. Second, we are concerned with the combination of different elements, going beyond the discussion of correlations between single elements (Ragin, 1987). By using a mixed-method approach, we support in this paper the notion that Fuzzy Set Qualitative Comparative Analysis(fsQCA)should be complemented with necessary condition analysis (NCA) (Torres et al., 2021). Our results show that there are three main combinations of digital entrepreneurial ecosystem elements in promoting high-quality growth in rural China. Third, scholars have already discussed the role of digital technologies in achieving sustainable and social innovative development. We expand this research by examining how digitalization promotes social transformation, especially in rural areas where development is relatively backward. Our findings also provide Chinese ideas for expanding research on the impact of digital innovation on rural entrepreneurship.

The next section provides the literature review on digital entrepreneurial ecosystems and total factor productivity. Thereafter, the research framework and methods are described. Then, the results of configuration analysis are presented, followed by the findings and main conclusions. Finally, implications for policymakers and researchers are drawn.

LITERATURE REVIEW

In recent years, an increasing number of scholars have introduced the concept of an ecosystem from biology into management research to study complex environments, resulting in theories such as digital and entrepreneurial ecosystems. Entrepreneurial ecosystems originate from a group of interdependent participants who engage in productive entrepreneurial activities and enhance performance through relationships and resource flows between subjects (Spigel, 2017). With the disruptive influence of digital technologies on traditional entrepreneurship models, many scholars have begun to consider the role of digital technology in entrepreneurial ecosystems. Sussan and Acs (2017) first proposed the conceptual framework of digital entrepreneurial ecosystems by integrating the concepts highlighting the positive roles of digital infrastructure governance, user citizenship, entrepreneurship, and the marketplace. Song (2019) believed that digital technology's potential impact on entrepreneurial ecosystems is manifested in the spatial dimension. Entrepreneurial ecosystems, revolving around enterprises, exhibit characteristics such as network-based regional features and generate platform-based symbiotic and competitive relationships (Cavallo et al., 2019). The openness of digital technology reduces the technological barriers and market entry risks for businesses, allowing factors to flow more freely across regions and borders, increasing the likelihood of entrepreneurial success and improving entrepreneurial quality (Elia et al., 2020). Zhu et al. (2020) examined the dynamic evolution of Hangzhou Yunqi Town in China in the form of case studies and found that digital entrepreneurial enterprises, users, and governments, as core subjects, could provide support for the continuous evolution of digital entrepreneurial ecosystems.

Digital entrepreneurial ecosystems have an impact on organizational and industrial development. Digital technology promotes organizational and industrial transformation through the reconstruction of production factors. Scholars have focused on the core subjects of digital entrepreneurial ecosystems (i.e., digital entrepreneurial enterprises) and have studied the impact of enterprise digital transformation on TFP. For example, Hao et al. (2022) found that the integration of the digital economy with other industries could improve production efficiency and product quality. Enterprise digital transformation has a positive effect on TFP through the spillover effects of knowledge capital and human capital. Scholars have focused on the digital entrepreneurial environments of digital entrepreneurial ecosystems, including the digital economic environment,

digital technology environment, and digital institutional environment. Jin et al. (2023) found that digital technology is the driving force of the digital economy, triggering multidimensional breakthroughs in production factors and giving rise to new technologies, capital, and labor, which improves TFP directly. We emphasize, however, that digital entrepreneurial ecosystems have an impact on the quality of regional development. And rural areas are more significantly constrained by information, capacity, resources, and capital. Market activities supported by digital technology can help fill the gap in rural development.

In terms of research methods, the literature focuses on the effects of single factors on TFP, treating each factor as independent or with partially related components such as by examining the positive and negative linear relationships between factor quality, infrastructure, structural transformation (Gong et al. 2023; Liu & Ling, 2020), digital technology (Jin et al., 2023), institutional environment (Jiao et al., 2015), and TFP, or by studying the varying relationships from a perspective of changing weights. When nonlinear complex phenomena emerge, it is necessary to introduce new theories and methods adapted to complex systems perspectives (Rihoux & Ragin, 2009). Analyzing the synergy of different factors within complex systems from a comprehensive and systematic perspective is of great significance (Misangyi et al., 2017) because it can answer questions such as which combinations of factors can produce the desired results and which lead to the absence of results.

Through a review of the literature, we observed that scholars have conducted extensive research on the theory of digital entrepreneurial ecosystems and have preliminarily explored the impact of digital entrepreneurial enterprises and digital entrepreneurial environments on TFP at the organizational and industrial levels. The following shortcomings remain. First, research on digital entrepreneurial ecosystems mainly adopts theoretical analysis or single-case qualitative research methods, with fewer empirical analyses based on multiple-case samples. Second, the study of TFP focuses on single influencing factors, making it difficult to comprehensively explain the complex driving mechanisms of TFP. Therefore, in this paper, we analyze the relationships between various factors in digital entrepreneurial ecosystems and TFP based on a configurational perspective, combining fsQCA and NCA methods to reveal the complex mechanisms and different paths of multifactor synergy that influence high-quality rural development in the ecosystem. We intend to address the following questions:

1. What are the influence paths generated by the combination of various factors in digital entrepreneurial ecosystems?
2. To what extent are these factors necessary for producing high TFP in rural areas?
3. What kinds of rural digital entrepreneurial ecosystems can sufficiently generate high TFP?
4. What mechanisms drive this outcome?

THEORETICAL BACKGROUND AND RESEARCH FRAMEWORK

Pathways and Mechanisms of Total Factor Productivity Realization

Modern economic growth theory suggests that TFP is the driving force behind sustainable national economic growth, which can no longer be achieved solely by improving TFP through traditional factors. Starting from the neoclassical production function, Solow (1957) discovered the "Solow residual" in his calculations, which piqued scholars' interest in unexplained portions of economic growth. Current research on TFP indicates that technological drivers (Jin et al., 2023), structural transformation (Gong et al. 2023; Liu & Ling, 2020), and transaction cost reduction (Du et al., 2022) all influence TFP. In this paper, we analyze how technological drivers, structural transformation, and transaction cost reduction affect TFP in a complex way, and, based on these mechanisms, we

analyze from a configurational perspective how digital entrepreneurial ecosystems promote the improvement of TFP.

Technological Drivers

Based on the Cobb-Douglas production function and the Solow residual, technological progress and efficiency improvements both contribute to the promotion of TFP (Chen & Huang, 2022; Huang et al., 2019). Li (2016) distinguished between technological progress and technological efficiency. First, technological progress promotes production efficiency through technological innovation, which is influenced by factors such as funding and human capital. Second, technological efficiency improves lagging firms' productivity by utilizing existing technologies. In addition to independent innovation, an important approach for China to improve its TFP under the government-led reform model is to achieve economic growth by attracting foreign investment, absorbing new technologies, and innovating after digestion. New growth theory also highlights the positive role of government regulation in technological efficiency. Therefore, from the technology-driven perspective, digital entrepreneurial ecosystems can not only promote rural human capital investment and technological innovation but also reasonably manage knowledge spillover and value creation through the regulatory institution to improve TFP in rural regions.

Structural Transformation

As a traditional driver of TFP improvement in China, structural transformation has two effects. First, structural upgrading enhances productivity through industry integration and the social coordination costs of traditional industries decrease, thereby increasing performance. Second, structural optimization promotes demand and consumption upgrading, empowering knowledge and technology innovation. Rapid structural transformation has a restraining effect on TFP, however, mainly manifested as industrial hollowing (Liu & Ling, 2020), which leads to resource mismatch and reduced productivity (Du et al., 2022; Hsieh & Klenow, 2009; Mao et al., 2023). Based on the structural transformation perspective, digital entrepreneurial ecosystems not only promote the transformation of rural traditional industries through the optimal allocation of resources but also promote integration between rural industries to improve TFP.

Reduction of Transaction Costs

All transaction methods and institutions have transaction costs, which affect resource allocation (Coase,1937). Transaction cost theory can be used to explain the transformation of economic activities between enterprises and markets. Saving transaction costs to improve efficiency is an important reason for the formation of enterprises. The application of new technology breaks the barrier of time and space to ensure the reduction of transaction costs. In addition, effective institutional constraints as "visible hands" can provide market traders with definite expectations and convey information and trust, whereas transaction costs determine the performance of economic operations. Based on the transaction cost perspective, digital entrepreneurial ecosystems not only encourage market entities to obtain reasonable returns through independent transactions but also reduce transaction costs under institutional constraints to improve TFP in rural regions.

Digital Entrepreneurial Ecosystems and Total Factor Productivity

Following the introduction of the digital entrepreneurial ecosystem theory, we have integrated various elements of digital entrepreneurship into a unified analytical framework, laying the theoretical foundation for us to investigate the impact of different factors on TFP from a holistic perspective. Digital infrastructure conditions are fundamental for the emergence of digital entrepreneurship, often involving government participation. The formal and informal institutional environment guides people to engage in productive digital entrepreneurship and stimulates widespread and in-depth market participation of digital users. Digital enterprises often require

substantial and long-term financial support in their initial stages, making the financial environment a crucial resource for entrepreneurs. Digital entrepreneurship cannot be achieved without a large number of professional technical personnel, making the talent environment another essential resource for digital entrepreneurial ecosystems. We specifically elaborate on the impact of six elements of digital entrepreneurial ecosystems on TFP: the digital infrastructure, digital market environment, financial environment, level of digital human resources, government service environment, and informal institution.

Digital Infrastructure and Total Factor Productivity

As a socially embedded mechanical system, digital infrastructure integrates the novel factor of data with other key production factors in the countryside, helping improve existing technological conditions and achieve an increase in TFP (Henfridsson & Bygstad, 2013). As a basis for regional transformation, digital infrastructure helps the countryside realize the reallocation of elements and promote the agglomeration of digital innovative and entrepreneurial activities (Zhang et al., 2022). Digital infrastructure allows participants who can influence rural development to contribute freely with few boundaries, facilitates the formation of a social cooperation network, and improves transaction efficiency. Thus, digital infrastructure construction can help enhance regional technological innovation vitality, achieve leaps in decision-making and transaction efficiency, and improve TFP in rural regions.

Digital Market Environment and Total Factor Productivity

As the "invisible hand," the digital market changes transaction costs and knowledge spillovers, thereby impacting TFP. A dynamic digital market in the countryside provides enterprises with an open and liberal environment, reducing market entry costs and encouraging mutual learning among enterprises under the influence of competition and price mechanisms, driving technological innovation. In addition, the digital market environment plays an important role in promoting the transformation of the rural industrial chain. Optimizing the market environment in the countryside can enable the market mechanism to play a forcing role, promote rural industrial transformation, and enhance market vitality, increasing TFP in rural regions.

Financial Environment and Total Factor Productivity

The financial environment has a significant impact on the resource allocation of enterprises, especially small- and medium-sized enterprises, which may play a crucial role in enhancing TFP (Beck & Demirguc-Kunt, 2006). An inclusive financial environment effectively promotes capital flow from urban centers to the countryside, breaking traditional credit constraints and financial exclusion and increasing the availability of rural financial resources, which can contribute to rural technological innovation and industrial development. In addition, the financial environment can also overcome imperfections in the capital market caused by information asymmetry, reducing corporate financial costs. A favorable level of financial service in the countryside can lower the financial risks faced by rural industries engaged in upgrading, reduce transaction costs between participants, and ultimately increase TFP in rural regions.

Digital Human Resources and Total Factor Productivity

Because of the scarcity of rural human capital, staff with certain managerial and technical skills are needed in the countryside (Miles & Morrison, 2020). A good quantity and quality of digital human resource enhances the capacity for rural technological innovation, contributing to high-quality rural development. Those human resources that are conducive to creating economic value are called digital human capital. Digital transformation in the countryside needs to optimize the structure of human capital. A higher level of digital human resources can improve rural TFP through knowledge innovation and the spillover effect of knowledge capital (Clarysse et al., 2014). Improving the level of digital

human resources means investing in higher-quality labor resources, and effectively enhancing TFP in rural regions through structural transformation.

Government Service Environment and Total Factor Productivity

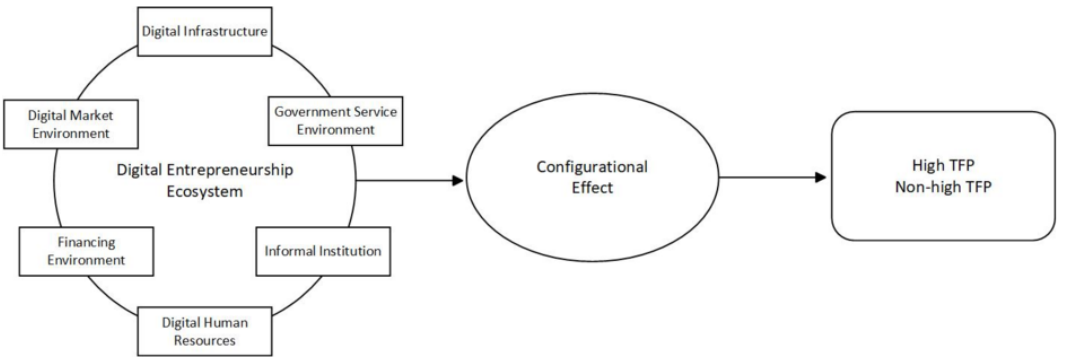
As the first fundamental pillar of digital entrepreneurial ecosystems, government, especially economic-related government institutions, helps efficiently allocate resources in the countryside. Economic growth and TFP are achieved by attracting foreign investment, absorbing new technologies, and innovating after assimilation with government support and guidance. Rules and regulations made by the government provide participants with certain expectations and constraints and play a role in transmitting information and reducing transaction costs. The government's expenditures affect market transaction costs, providing support for regional research and development by optimizing fiscal and tax measures (Li, 2016). As an important formal institutional support, the government service environment can promote rural technological innovation, industrial transformation, and market transactions that influence TFP in rural regions.

Informal Institution and Total Factor Productivity

Informal institution related to social capital have a significant impact on human behavior and welfare (Rivera et al., 2019). Owing to more prominent social embeddedness, rural social capital is closely related to rural sustainable development because the unique attributes of rural areas may not lie in innovation in the traditional sense but in their relation to community benefits (Peredo & Chrisman, 2006). On the one hand, informal institution plays an essential role in consumption, risk-taking, and value creation. Individuals and organizations can expand their social networks, promote imitative innovation, and reduce transaction costs. On the other hand, the institution can restrain the behavior of participants in digital entrepreneurial ecosystems. As an important part of entrepreneurial ecosystems in the countryside, the informal institutional environment can influence institutional choices and factor input in the countryside, affecting TFP.

Related research has not revealed how the interaction of various elements in digital entrepreneurial ecosystems affects TFP. In the following sections we analyze the interactions among various elements and complex causal relationship in digital entrepreneurial ecosystems from a configurational perspective, exploring the pathways for enhancing TFP in rural areas. Accordingly, we introduced the QCA method with a configurational perspective combined with the NCA method to investigate how the configurational effects of multiple factors in digital entrepreneurial ecosystems influence TFP as shown in Figure 1.

Figure 1. Mechanisms through which digital entrepreneurial ecosystems affect TFP of rural areas



METHODS

Research Methods

Dul (2016) proposed necessary condition analysis (NCA) as a research method for identifying conditions in data that are necessary but not sufficient. The NCA method can quantitatively demonstrate the level of antecedent conditions required to achieve a certain level of the outcome variable through the effect size and bottleneck level. Qualitative comparative analysis (QCA) is a method of configurational analysis based on Boolean algebra that examines the sufficient and necessary subset relationships between antecedent conditions and outcomes, enabling a holistic exploration of how complex social issues occur owing to multiple concurrent causes (Fiss, 2011). QCA conceptualizes causal relationships as complex causality characterized by equivalence, asymmetry, and multiple concurrent causes, making it suitable for exploring the complex sufficiency and necessity relationships between digital entrepreneurial ecosystems and TFP.

Drawing on Dul et al. (2020), the combination of NCA and fsQCA has greater value. Therefore, in this paper we first use the NCA method to test whether each element in a specific digital entrepreneurial ecosystem is a necessary condition for affecting TFP, and then we employ fsQCA to examine the robustness of the NCA results. Next, using the holistic perspective of fsQCA, we conduct cross-case comparative analysis to explore which combinations of antecedent factors lead to high or non-high TFP, thereby revealing the complex causal mechanisms by which digital entrepreneurial ecosystems affect rural high-quality development. Furthermore, fsQCA employs Boolean algebra rather than traditional regression methods, so it does not result in omitted variable bias and is better suited to the dynamic complexity of the real world.

Sample and Data Sources

We used the list of the National Rural Revitalization Demonstration Counties published by China's Ministry of Agriculture and Rural Affairs in 2022 as the research objects and selected 60 counties as the research sample based on data availability, thus meeting the case quantity requirements of QCA. These cases cover most provincial administrative regions and municipalities in China, with considerable heterogeneity, satisfying the diverse case requirements and facilitating the analysis of how different regions can adapt to local conditions and pursue their own high-quality development paths.

Condition variables are derived from the Peking University Digital Financial Inclusion Index (Guo et al., 2020), the Digital Rural County Index database from Peking University's Institute of New Rural Development and Ali Research Institute, the Seventh National Population Census data, the China County Statistical Yearbook, and various provincial and municipal statistical yearbooks. The data for the result variable, rural TFP, comes from the China County Statistical Yearbook, the China Rural Statistical Yearbook, provincial and municipal statistical yearbooks, and the CEInet statistics database. We filled in missing data using the mean method or difference method of historical data. All data used in this paper are from 2020. In addition, we conducted qualitative analysis of the classic case counties' government documents and media reports in light of the research findings.

Measurement and Calibration

Outcome Variable

Data envelopment analysis (DEA) is generally used to evaluate the production efficiency of decision-making units through inputs and outputs. We employed the DEA-SBM model (Tone, 2001) and used MaxDEA software to measure the TFP levels of 60 sample counties. According to the basic conditions of the SBM model, we selected input and output indicators. Input indicators include capital investment, labor input, and energy input. Capital investment is represented by the total fixed assets

of the whole society; labor input by the number of rural employed persons at the end of the year; and energy input by the rural electricity consumption of the whole society. We calculated some missing data for the current year by using the growth rate of the corresponding year and previous years' data, and we completed other missing values by using the mean method or difference method. Output indicators are represented by the regional GDP.

Conditional Variables

Elements of digital entrepreneurial ecosystems serve as first-level indicators, which we obtained by weighting the second-level indicators. We obtained basic indicators through multiple databases, statistical yearbooks, and other means. To unify dimensions, basic data are dimensionless and processed using the utility value method:

- **Digital Infrastructure:** We measured the digital infrastructure by using the rural digital infrastructure index from the Peking University Institute of New Rural Development's Digital Rural County Index including the information infrastructure index, digital financial infrastructure index, digital commercial landmark index, and basic data resource system index.
- **Digital Market Environment:** We measured the digital market environment using the rural economic digitization index from the Peking University Institute of New Rural Development's Digital Rural County Index including the digital production index, digital supply chain index, digital marketing index, and digital finance index.
- **Financial Environment:** Considering that China's financial system is still bank-dominated, and the capital market is gradually improving, we used the proportion of loans from financial institutions to GDP to reflect the development of the financial market environment.
- **Digital Human Resources:** We selected the percentage of employment in the information transmission, software, and information technology services industry in the total employed population in the countryside to represent the level of rural digital human resources.
- **Government Service Environment:** We measured the scale of government services by the proportion of government general budget expenditure to GDP, which is widely used in research. We measured the construction level of service-oriented government by the governance means index in the rural governance digitization index from the Peking University Institute of New Rural Development's Digital Rural County Index.
- **Informal Institution:** We chose social capital to measure informal institution. Information accessibility and social receptivity effectively characterize a region's social capital. We selected the per capita number of telephones, per capita number of social-welfare institutions (adoption-oriented institutions), and per capita number of beds to reflect the social capital of county-level regions.

Calibration

When calibrating antecedent conditions and results, considering that the elements of digital entrepreneurial ecosystems and TFP lack clear standards to define high and non-high, it is suitable to use relative location calibration based on the sample. Therefore, we adopted the direct calibration method, converting data into fuzzy-set membership scores (Ragin, 2008). Referring to previous research and the frequency distribution based on the sample, we set the three calibration points of complete membership, crossover point, and complete non-membership for the six condition variables and one result variable (TFP) as the 80th percentile, median, and 20th percentile of the descriptive statistics of the case sample, respectively. Calibration anchor points are shown in Table 1.

Table 1. Calibration anchors

Set	Fuzzy Set Calibration		
	Complete Non-Membership	Crossover Point	Complete Membership
TFP	0.366	0.523	0.742
Digital Infrastructure	0.379	0.519	0.685
Digital Market Environment	0.081	0.132	0.235
Financial Environment	0.075	0.170	0.298
Digital Human Resources	0.077	0.121	0.211
Government Service Environment	0.242	0.435	0.567
Informal Institution	0.116	0.201	0.374

RESULTS

Necessary Conditions Analysis

We used the NCA method to analyze the necessary antecedent conditions (see Table 2). NCA provides two methods: ceiling regression (CR) and ceiling envelopment, which are used to deal with continuous variables and discrete variables, respectively, and derive the corresponding accuracy, upper limit area, range, effect size d, and P-values. The effect size d represents the necessity level of the antecedent conditions, with a range of [0, 1]; the higher the d value, the greater the effect. When the effect size d is greater than 0.1 and the P-value indicates a significant effect ($P < 0.01$), the antecedent condition is considered to be a necessary condition for producing the outcome. The NCA results showed that the necessity effects of all elements except digital human resource were not significant ($P > 0.01$) and do not constitute necessary conditions for TFP. Although the necessity effect of the digital human resource in the CR test was significant, the effect size was so small ($d = 0.032 < 0.1$) that it cannot constitute a necessary condition.

Table 2. NCA method results of single necessary condition analysis

Conditions	Methods	Accuracy	Ceiling Zone	Scope	Effect Size (d)	P-Value
Digital Infrastructure	CR	98.3%	0.060	0.734	0.082	0.346
	CE	100%	0.118	0.734	0.118	0.238
Digital Market Environment	CR	100%	0.006	0.798	0.007	0.722
	CE	100%	0.012	0.798	0.015	0.610
Financial Environment	CR	96.7%	0.016	0.798	0.020	0.392
	CE	100%	0.015	0.798	0.019	0.548
Digital Human Resources	CR	95%	0.025	0.780	0.032	0.014
	CE	100%	0.012	0.798	0.016	0.318
Government Service Environment	CR	96.7%	0.059	0.614	0.096	0.272
	CE	100%	0.086	0.614	0.140	0.148
Informal Institution	CR	96.7%	0.016	0.433	0.037	0.297
	CE	100%	0.016	0.454	0.038	0.387

To cross-validate the results and supplement the NCA method, we further adopted the QCA method for individual condition necessity tests, the results of which are shown in Table 3. The consistency judgment standard for QCA necessary conditions mostly adopts a threshold of 0.9 (Fiss, 2011). As the table shows, the consistency of the necessity tests for each element of digital entrepreneurial ecosystems was less than 0.9. This indicates that the QCA method's test results are consistent with the NCA method's results, meaning there is no single necessary condition for generating high or non-high TFP.

The consistency judgment standard for QCA necessary conditions mostly adopts a threshold of 0.9 (Fiss, 2011). As the table shows, the consistency of the necessity tests for each element of digital entrepreneurial ecosystems was less than 0.9. This indicates that the QCA method's test results are consistent with the NCA method's results, meaning there is no single necessary condition for generating high or non-high TFP.

Configuration Analysis

We employed the fsQCA method to analyze data from 60 county-level cases. Referring to existing research, we set the case frequency threshold to 1 when constructing the truth table (Du & Jia, 2017), the original consistency threshold to 0.8 (Fiss, 2011), and PRI consistency threshold to 0.75. Core and peripheral conditions are identified by comparing parsimonious and intermediate solutions. Four configurations (see Table 4) that produced high TFP (S1, S2, S3, S4) and one configuration that produced non-high TFP (NS1) were derived from the analysis with consistencies of 0.902, 0.933, 0.842, 0.897, and 0.806, respectively. Overall consistency was 0.927 and 0.806, which is close to ideal and meets the standard of greater than 0.8 used in most current research (Fiss, 2011). The coverage indicates that each configuration corresponded to actual cases, providing substantial explanations for the paths that produce high or non-high TFP.

Configurations That Produce High Total Factor Productivity

Figure 2 illustrates four configurations that produce high TFP (S1, S2, S3, and S4), with S1 and S2 sharing the core conditions of digital infrastructure, financial environment, and government

Table 3. fsQCA necessary condition analysis for a single condition

Independent Variables	Outcome Variable	
	High TFP	Non-High TFP
Digital Infrastructure	0.576163	0.500498
~ Digital Infrastructure	0.532641	0.607368
Digital Market Environment	0.581553	0.513110
~ Digital Market Environment	0.536960	0.604381
Financial Environment	0.585269	0.520080
~ Financial Environment	0.560027	0.623963
Digital Human Resources	0.603950	0.528709
~ Digital Human Resources	0.542015	0.615997
Government Service Environment	0.504185	0.579157
~ Government Service Environment	0.620020	0.543976
Informal Institution	0.560094	0.526718
~ Informal Institution	0.557750	0.590110

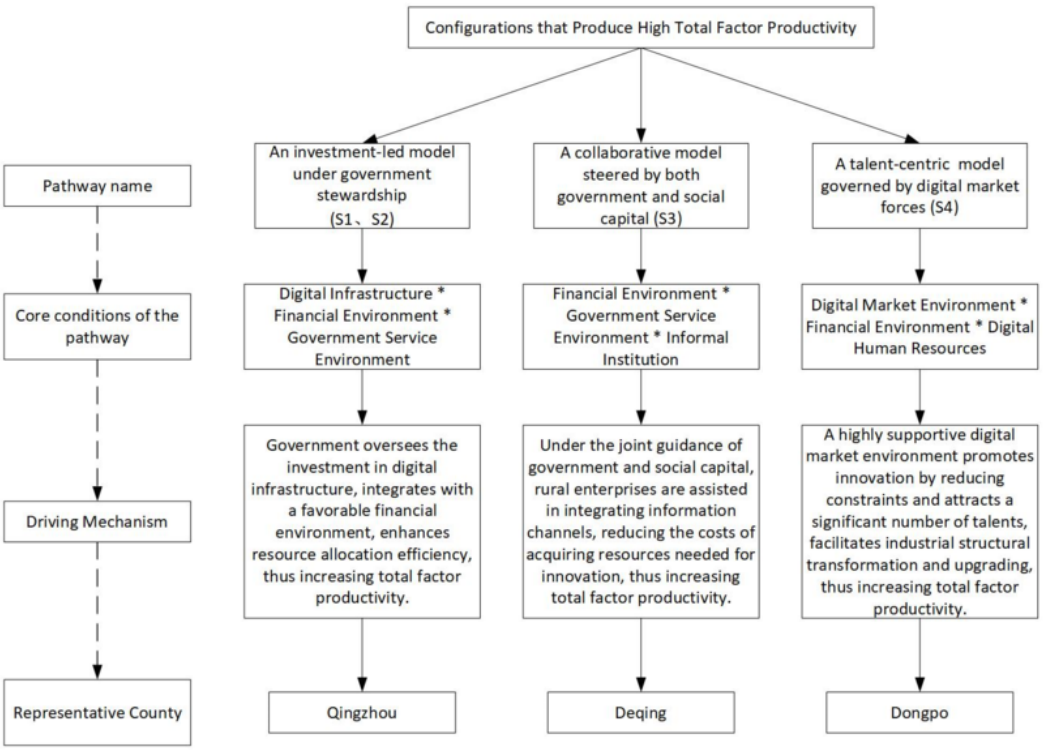
Note: "~" refers to "not" in logic

Table 4. Configurations that generate high and non-high TFP

Independent Variables	High TFP				Non-High TFP
	S1	S2	S3	S4	NS1
Digital Infrastructure	●	●		⊗	X
Digital Market Environment	⊗		⊗	●	⊗
Financial Environment	●	●	●	●	⊗
Digital Human Resources		⊗	X	●	⊗
Government Service Environment	●	●	●	X	●
Informal Institution	X	⊗	●	◦	⊗
Consistency	0.902	0.933	0.842	0.897	0.806
Raw Coverage	0.139	0.136	0.136	0.123	0.151
Unique Coverage	0.011	0.030	0.021	0.055	0.151
Solution Coverage	0.927				0.806
Solution Consistency	0.272				0.151

Note: ● represents the presence of core conditions and ◦ represents the presence of marginal conditions, ⊗ represents the absence of core conditions and X represents the absence of marginal conditions.

Figure 2. Configurations that produce high total factor productivity



Note. "*" represents "AND" in Boolean algebra.

environment. S3 combines the core conditions of the financial environment, governmental environment, and informal institution. S4 incorporates the digital market environment, financial environment, and digital human resources as core conditions. Based on the core conditions of the four configurations and the explanatory logic of their corresponding cases, we identified three following pathways for high rural TFP.

An Investment-Led Model Under Government Stewardship

Configurations S1 and S2 reveal an investment-driven path under government leadership, with core conditions of digital infrastructure, financial environment, and government environment. Digital entrepreneurial ecosystems are led by a highly supportive government environment (including a high government service scale and a high service-oriented government construction level), which optimizes and upgrades rural digital infrastructure and integrates resources with a favorable financial environment to achieve high TFP and high-quality rural development. In China, the central and local governments put forward a series of government digital initiatives (Wang et al., 2023), which can improve economic and social development. Prior studies suggest that government can affect enterprise innovation and entrepreneurial activities through various means such as innovation programs, information and technology resources, tax incentives and financial support (Li et al., 2018; Torres & Godinho, 2021). Government initiatives not only bring attention to the opportunities of digital entrepreneurship (Dai et al., 2020) but also induce resource accumulation within a particular region (Lazzarini, 2015). These influences are prominent in rural areas. Effective government can alleviate financial constraints for enterprises and improve resource allocation efficiency. It can also promote rural digital optimization and upgrading by expanding investments in digital infrastructure, which may improve TFP by substituting for some human resource input, alleviating resource mismatches, and improving technological innovation. The typical cases in China include Qingzhou in Shandong Province, Liuyang in Hunan Province, and Tongnan in Chongqing. As one of the top 100 county-level economic entities in China, Qingzhou relies on the government's construction of digital infrastructure and proactive policies pertaining to financial institutions, developing abundant digital entrepreneurship resources, fostering numerous digital entrepreneurship enterprises, and creating a high-quality rural development promoting industrial integration and digital transformation.

A Collaborative Model Steered by Government and Social Capital

The government and social capital co-driven type, discovered in configuration S3, has core conditions of financial environment, governance environment, and informal institution. Under favorable combinations of environments, regions are identified by higher information accessibility, social tolerance, and social trust, helping rural enterprises effectively integrate information channels and acquire the scarce resources required for innovation with low costs (Tong et al., 2021). The formation and development of Taobao villages coincides with the driving conditions of this path. It is spearheaded by returning young people, who obtain funding or loans through the support of local governments and "guanxi" of acquaintances to start their businesses locally and contribute to digital entrepreneurial clusters. Prior studies propose that different from rule-based market economies like the United States, e-commerce activity in China is more relationship-based (Martinsons, 2008). Informal institution, such as social trust and capital can significantly impact farmers' decisions to adopt e-commerce (Liu et al., 2021). Typical cases in China influenced by this driving mechanism include Xiangshan and Deqing in Zhejiang Province. Zhejiang Province has the most extensive coverage of Taobao villages, with Deqing as an example. As early as 2015, Deqing focused on three major fields of rural e-commerce including manufacturing, services, and agriculture, thereby generating high rural digital entrepreneurship vitality. Under the impetus of neighborhood relations, policy environment support, and other conditions, professional e-commerce villages were formed. The coupling of government and social capital drives industrial agglomeration to form economies of scale, creating industrial

cluster models like the Taobao villages, fully utilizing regional industrial advantages, and promoting high-quality rural development.

A Talent-Centric Model Governed by Digital Market

The talent-driven model under digital market dominance, identified by configuration S4, is characterized by core conditions such as the digital market environment, favorable financial environment, and digital human resources. A highly supportive digital market environment signifies a more liberal market trading and digital entrepreneurial environment with fewer constraints and a more complete industrial chain. And market-oriented financial structure promotes innovation through capital accumulation and reducing financial constraints. The highly supportive digital market environment and financial environment attract a large amount of digital talent for employment and entrepreneurship activities, improving the resource allocation efficiency of rural enterprises, then achieving high-quality development. Talent is one of the essential factors affecting developing regional innovation capability (Huang et al., 2022). Scuotto et al. (2023) proposed one concept of digital humanism that involves emphasizing the relevance of human skills. Human characteristics and capabilities nurture knowledge innovation and digital entrepreneurial activities. A typical case in China under this driving mechanism is Dongpo, Sichuan Province. With its vibrant market environment, private economy there supports half of the regional economy. To sustain the development of private enterprises, Dongpo strengthens bank-enterprise docking, expands financial channels, and creates a favorable financial environment. Due to well-developed market and financial environments, Dongpo attracts a large amount of digital talent, promotes the implementation of digital entrepreneurship and the transformation of industrial structures, successfully creating an engine for high-quality development, ultimately improving rural TFP.

Configurations for Non-High Total Factor Productivity

We also examined the digital entrepreneurship ecology that leads to non-high TFP, identifying one distinct configuration. According to the results of configuration NS1, when the core conditions of the digital market environment, financial environment, digital human resource level, and informal institution is absent, and the digital infrastructure is a missing peripheral condition, rural TFP is not high. This indicates that relying solely on government support cannot effectively improve rural TFP and it is necessary to activate market vitality and provide supporting resources.

Robustness Test

To test the robustness of the results (Du et al., 2022; Zhang & Du, 2019), we did the following. First, increasing the case frequency threshold from 1 to 2, configurations are yielded (see Table 5) that are largely consistent with the existing configuration, S3. The increased case frequency threshold reduces the number of cases, eliminating configurations S1, S2, and S4, and generating new configurations with greater core explanatory power that display a set relationship with existing configurations. Second, by lowering the PRI consistency from 0.75 to 0.7, the resulting configurations (see Table 6) encompass the existing configurations and generate a new one, S5. Third, adjusting the calibration anchor points (full membership, crossover point, and full non-membership) to the 75th percentile, median, and 25th percentile, respectively, the resulting configurations (see Table 7) after recalibration are essentially consistent with the existing configurations. The robustness testing supports the relative robustness of our results (Ragin, 2008).

Table 5. Robustness test of raising the frequency threshold

Independent Variables	High TFP (Frequency Threshold = 1)				High TFP (Frequency Threshold = 2)
	S1	S2	S3	S4	S2
Digital Infrastructure	●	●		⊗	●
Digital Market Environment	⊗		⊗	●	◦
Financial Environment	●	●	●	●	◦
Digital Human Resources		⊗	✗	●	⊗
Government Service Environment	●	●	●	✗	◦
Informal Institution	✗	⊗	●	◦	⊗
Consistency	0.902	0.933	0.842	0.897	0.942
Raw Coverage	0.139	0.136	0.136	0.123	0.115
Unique Coverage	0.011	0.030	0.021	0.055	0.115
Solution Coverage	0.927				0.942
Solution Consistency	0.272				0.115

Note: ● represents the presence of core conditions and ◦ represents the presence of marginal conditions, ⊗ represents the absence of core conditions and ✗ represents the absence of marginal conditions.

Table 6. Robustness test of lowering PRI value

Independent Variables	High TFP (PRI = 0.7)				
	S1	S2	S3	S4	S5
Digital Infrastructure	●		●	⊗	●
Digital Market Environment	⊗	⊗		●	⊗
Financial Environment	●	●	●		✗
Digital Human Resources		✗	⊗	●	✗
Government Service Environment	●	●	●	✗	●
Informal Institution	✗	●	⊗	◦	
Consistency	0.928	0.937	0.933	0.895	0.879
Raw Coverage	0.108	0.120	0.136	0.125	0.114
Unique Coverage	0.014	0.050	0.049	0.072	0.050
Solution Coverage	0.908				
Solution Consistency	0.353				

Note: ● represents the presence of core conditions and ◦ represents the presence of marginal conditions, ⊗ represents the absence of core conditions and ✗ represents the absence of marginal conditions.

CONCLUSION AND IMPLICATIONS

Research Conclusions

Optimizing the digital entrepreneurship environment to promote TFP growth has become a focal point in research on high-quality rural development. Combining the NCA, QCA, and DEA methods, we explored multiple paths of digital entrepreneurial ecosystems formed by configurations of digital

Table 7. Robustness test of changing calibration anchors

Independent Variables	High TFP (Changing Calibration Anchors to 75th Percentile, Median, and 25th Percentile)			
	S1	S2	S3	S4
Digital Infrastructure	●		●	⊗
Digital Market Environment	⊗	⊗		●
Financial Environment	●	●	●	●
Digital Human Resources		✗	⊗	●
Government Service Environment	●	●	●	✗
Informal Institution	✗	●	⊗	◦
Consistency	0.928	0.937	0.933	0.912
Raw Coverage	0.108	0.120	0.136	0.094
Unique Coverage	0.014	0.055	0.049	0.055
Solution Coverage	0.927			
Solution Consistency	0.272			

Note: ● represents the presence of core conditions and ◦ represents the presence of marginal conditions, ⊗ represents the absence of core conditions and ✗ represents the absence of marginal conditions.

infrastructure, the digital market environment, the financial environment, digital human resources, the government service environment, and informal institution to understand the promotion of TFP from a configurational perspective, and we made three main findings.

First, the necessity analysis of the NCA and QCA methods revealed that individual elements of digital entrepreneurial ecosystems do not constitute necessary conditions for high or non-high TFP. This suggests that any one element of digital entrepreneurial ecosystems has a limited impact on promoting rural TFP. Optimizing the financial environment, however, plays a universal role in generating high TFP in rural areas, highlighting the importance of continuously improving the financial environment, reducing financial constraints for enterprises, especially small- and medium-sized ones, and emphasizing the critical role of a favorable financial environment in promoting high-quality rural development. The literature suggests that all digital entrepreneurial ecosystem elements are necessary to high development (Stam & Van de Ven, 2019). In contrast, our results show that some of the elements might not always be necessary under all configurations. As mentioned in prior studies (see, e.g., Lian et al., 2023), digital inclusive finance plays an indispensable role in developing rural digital entrepreneurial ecosystems.

Second, in line with past research (see, e.g., Torres et al.,2021), we discuss different configuration of entrepreneurial ecosystem elements but put the context on digitalization in Chinese rural regions, where it is of a unique situation and resource endowment. We identified three driving paths to high TFP in rural areas: an investment-led model under government stewardship, a collaborative model steered by both government and social capital, and a talent-centric model governed by digital market forces. These findings reflect the diverse paths to high-quality development, indicating that different regions are at different stages of development and have varied mechanisms driving TFP. Generally speaking, Chinese digital government initiatives promote building digital infrastructure, offering new digital entrepreneurship opportunities for rural areas and shaping a favorable market environment that induces external resources (Eklinder-Fricke, 2017; Wang et al., 2023). Chinese rural societies are more relationship-based, rather than rule-based (Martinsons, 2008), this is good condition for digital entrepreneurship diffusion. Knowledge-driven innovation has assumed a crucial role in the new digital era (Scuotto et al.,

2023) in the rural market. These research findings highlight the particularity of China's rural context, thus bringing new inspirations to the previous literature.

Third, we found a driving path for non-high TFP in rural areas: when core conditions such as the digital market environment, financial environment, digital human resource levels, and informal institution is absent, and digital infrastructure is marginally missing, high-quality development cannot be achieved even with guarantees of government expenditure.

Theoretical and Practical Implications

Theoretical Implications

We contribute to the research findings related to digital innovation. The application of digital technology has significantly affected the high-quality development of the countryside in China, which reveals the prominent role of digital innovation in promoting social transformation and creating social value (George et al., 2021; Tuukka et al., 2023). Specifically, in rural areas, digital initiatives such as the construction of digital infrastructure, the creation of a digital market environment, and the cultivation of digital skills, help BOPs break the constraints of resources and capabilities and allow participants who can influence rural development to contribute freely with fewer boundaries, increasing rural TFP and narrowing the gap between urban and rural regions. The findings emphasize the inclusiveness of digital innovation that previous studies have ignored (see, e.g., Roberts et al., 2017). Additionally, we hold that transformation driven by digital innovation in the countryside cannot happen without the joint participation of technology, information, resources, knowledge, capital, and other factors (Huang et al., 2022), which provides a new research perspective on the occurrence of digital innovation.

We expand the existing research on digital entrepreneurial ecosystems. The application of digital technology has significantly influenced entrepreneurial activities and has supported the formation of digital entrepreneurial ecosystems. As an emerging hot topic in recent years (Sussan & Acs, 2017), most research focused on the organizational level, whereas few studies focused on the regional level, ignoring issues pertaining to the countryside. In view of the uniqueness of the rural environment (Miles & Morrison, 2020), we argue that it is necessary to study the impact of these ecosystems on rural development. Because different villages have evolved various digital entrepreneurial ecosystems based on the complex system view, there are multiple paths of high-quality rural development, but few studies have focused on the relationship between the rural digital entrepreneurial ecology and rural development from the perspective of complexity. TFP is one of the core components of the promotion of high-quality rural development. We propose that the digital entrepreneurial environment is a comprehensive ecosystem with multiple paths to optimize the digital entrepreneurial environment, rather than a single optimal equilibrium (Stam & Van de Ven, 2019). In addition, technology, structural transformation, and transaction costs provide an explanatory mechanism for how the digital entrepreneurship ecology affects rural TFP (Dul et al., 2020). We expand the application of the digital entrepreneurial ecosystem theory in multiple factor relationships and provide new insights for the coupled study of digital entrepreneurial ecosystems and TFP.

We also respond to the call of the complex systems view for a "combinatorial" methodology. The complex systems view holds that the economic system has complex characteristics such as the interdependence of multiple factors. By adopting a configurational perspective and combining the QCA, NCA, and DEA methods, we examined whether single factors in digital entrepreneurial ecosystems constitute necessary conditions and asked what combinations of elements can achieve TFP improvement in the countryside. It is worth mentioning that QCA can analyze complex causal relationships of sufficient conditions, while NCA can more finely analyze necessary condition causal relationships. We support the notion that fsQCA should be complemented with NCA to better understand the necessary conditions (Torres & Godinho, 2021). This also provides a new insight and methodology for complex issues such as digital entrepreneurial ecosystems and high-quality development. Additionally, we chose China's countryside as the research context of a

complex system. The samples covered most provinces across the country, overcoming regional limitations and exploring complex pathways suitable for local conditions based on different regional development statuses.

Practical Implications

Our study provides some implications for the countryside aiming at high-quality development. Identifying necessary conditions has great value to policymakers. Considering the differences in the stages of development, resources, and technical endowments of different regions, the countryside should explore suitable pathways to achieve TFP improvement instead of hoping for the same development initiatives. Not all regions should blindly build digital infrastructure beyond their actual economic capabilities. A more practical approach is to integrate rural resources and rely on local advantageous industries to drive the transformation of other local enterprises to achieve high TFP in the countryside. This strategy could inspire policymakers in rural regions to identify the key points and difficulties in the construction of local digital entrepreneurial ecosystems and to judge, rather than blindly imitate, whether the comparative advantage comes from human capital, institutional governance, culture, markets, finance, infrastructure, or any combination of factors (Dul et al., 2020). When the relationship between the government and the market is properly handled, the interaction and combination of various elements within rural digital entrepreneurial ecosystems can generate optimal configurational effects. Only in this way can we maximize the role of digital entrepreneurial ecosystems in promoting high-quality rural development.

There are also some insights for participants in rural digital entrepreneurial ecosystems. All participants should take the initiative. Whether they are financial institutions, governments, digital organizations, or individuals with human capital, they should be clear about their respective divisions of labor and effectively contribute to developing an ecosystem. Financial institutions should realize the importance of financing for the survival and development of digital start-ups. An inclusive and efficient financial level can overcome the imperfections caused by information asymmetry in the capital market, reducing the external financing cost and easing financing constraints (Lian et al., 2023). Government departments should play a positive role in the transformation and development of the rural economy, promote the construction of a good digital innovation environment through institutional support, coordinate the allocation of entrepreneurial resources, and realize the vision of the digital countryside (Wang et al., 2023). Digital organizations should lead the development of digital entrepreneurial ecosystems; actively develop digital entrepreneurial activities through product, service, process, or business model innovation by focusing on demand and promoting the transformation of rural traditional industries. Individuals should cultivate digital skills through continuous learning, receive digital entrepreneurship education, integrate digital innovation knowledge, and give full play to the role of human resources and knowledge spillover in rural high-quality development (Srivastava & Shainesh, 2015).

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

There are some limitations that warrant further research. First, although we studied the impact of digital entrepreneurial ecosystems on TFP based on aspects such as infrastructure, markets, politics, human resources, financial environments, and informal institution, we did not examine how the interaction of multiple stakeholders within a digital entrepreneurial ecosystem (including digital users, relevant enterprises, and platforms) influences TFP. Second, because of the availability of county-level data and cases, we selected 60 samples from the list of National Rural Revitalization Demonstration Counties published by China's Ministry of Agriculture and Rural Affairs, focusing on cross-regional analyses of different areas, but it is not as conducive to qualitative analysis as case studies, which may affect the generalizability of the conclusions. Third, we only examined the static

relationship between digital entrepreneurial ecosystems and TFP. With the continuous accumulation of data, future scholars can further observe how changes in digital entrepreneurial ecosystems affect TFP dynamically.

AUTHOR NOTE

Xiaotong Liu and Chengshuang Qi contributed to the manuscript equally.

The authors of this publication declare there are no competing interests.

This study was funded by the National Social Science Foundation (Grant No. 22CGL006).

Correspondence concerning this article should be addressed to Yuhuan Xia, 72 Binhai Road, Ji Mo, Qingdao 266237. Email: xiayuhuan@sdu.edu.cn

REFERENCES

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: Establishing the framework conditions. *The Journal of Technology Transfer*, *42*(5), 1030–1051. doi:10.1007/s10961-016-9473-8

Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, *30*(11), 2931–2943. doi:10.1016/j.jbankfin.2006.05.009

Bosma, N., & Sternberg, R. (2014). Entrepreneurship as an urban event? Empirical evidence from European cities. *Regional Studies*, *48*(6), 1016–1033. doi:10.1080/00343404.2014.904041

Cao, K., & Birchenall, J. A. (2013). Institutions, technological change, and rural productivity: Evidence from China. *Journal of Development Economics*, *104*, 165–180. doi:10.1016/j.jdeveco.2013.06.001

Cavallo, A., Ghezzi, A., & Balocco, R. (2019). Entrepreneurial ecosystem research: Present debates and future directions. *The International Entrepreneurship and Management Journal*, *15*(4), 1291–1321. doi:10.1007/s11365-018-0526-3

Chen, S., & Huang, W. (2022). Innovation input-output and output-lagged input relationships of the next-generation information industry in China. *Information Processing & Management*, *59*(6), 103066. doi:10.1016/j.ipm.2022.103066 PMID:36061343

Clarysse, B., Wright, M., Bruneel, J., & Mahajan, A. (2014). Creating value in ecosystems: Crossing the chasm between knowledge and business ecosystems. *Research Policy*, *43*(7), 1164–1176. doi:10.1016/j.respol.2014.04.014

Coase, R. H. (1937). The nature of the firm. *Economica*, *4*(16), 386–405. doi:10.1111/j.1468-0335.1937.tb00002.x

Dai, W., Arndt, F., & Liao, M. (2020). Hear it straight from the horse's mouth: Recognizing policy-induced opportunities. *Entrepreneurship and Regional Development*, *32*(5-6), 408–428. doi:10.1080/08985626.2019.1640452

Darroch, J., & Miles, M. P. (2011). A research note on market creation in the pharmaceutical industry. *Journal of Business Research*, *64*(7), 723–727. doi:10.1016/j.jbusres.2010.08.002

Du, Y., & Jia, L. (2017). Configuration perspective and qualitative comparative analysis (QCA): A new avenue for management research. *Journal of Management World*, *6*, 155–167.

Du, Y., Liu, Q., Chen, K., Xiao, R., & Li, S. (2022). Ecosystem of doing business, total factor productivity and multiple patterns of high-quality development of Chinese cities: A configuration analysis based on complex systems view. *Journal of Management World*, *38*(9), 127–145.

Dubini, P. (1989). The influence of motivations and environment on business start-ups: Some hints for public policies. *Journal of Business Venturing*, *4*(1), 11–26. doi:10.1016/0883-9026(89)90031-1

Dul, J. (2016). Identifying single necessary conditions with NCA and fsQCA. *Journal of Business Research*, *69*(4), 1516–1523. doi:10.1016/j.jbusres.2015.10.134

Dul, J., Laan, E., & Kuik, R. (2020). A statistical significance test for necessary condition analysis. Sage Publications, 2.

Eklinder-Frick, J., & Åge, L. J. (2017). Perspectives on regional innovation policy-from new economic geography towards the IMP approach. *Industrial Marketing Management*, *61*, 81–92. doi:10.1016/j.indmarman.2016.07.005

Elia, G., Margherita, A., & Passiante, G. (2020). Digital entrepreneurial ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technological Forecasting and Social Change*, *150*, 150. doi:10.1016/j.techfore.2019.119791

Emery, M., & Flora, C. (2006). Spiraling-up: Mapping community transformation with community capitals framework. *Community Development (Columbus, Ohio)*, *37*(1), 19–35. doi:10.1080/15575330609490152

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420. doi:10.5465/amj.2011.60263120

Fu, X. L., Pervez, G., Nwamaka, O., & Xing, X. Q. (2023). Platform-based business model and entrepreneurs from Base of the Pyramid. *Technovation*, *119*, 119. doi:10.1016/j.technovation.2021.102451

George, G., Merrill, R. K., & Schillebeeckx, S. J. D. (2021). Digital sustainability and entrepreneurship: How digital innovations are helping tackle climate change and sustainable development. *Entrepreneurship Theory and Practice*, *45*(5), 999–1027. doi:10.1177/1042258719899425

Gong, M., Zeng, Y., & Zhang, F. (2023). New infrastructure, optimization of resource allocation and upgrading of industrial structure. *Finance Research Letters*, *54*, 54. doi:10.1016/j.frl.2023.103754

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly*, *19*(4), 1401–1418.

Hao, X., Wang, X., Wu, H., & Hao, Y. (2023). Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity? *Sustainable Development (Bradford)*, *31*(1), 360–378. doi:10.1002/sd.2397

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *Management Information Systems Quarterly*, *37*(3), 907–931. doi:10.25300/MISQ/2013/37.3.11

Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, *124*(4), 1403–1448. doi:10.1162/qjec.2009.124.4.1403

Huang, J., Cai, X., Huang, S., Tian, S., & Lei, H. (2019). Technological factors and total factor productivity in China: Evidence based on a panel threshold model. *China Economic Review*, *54*, 271–285. doi:10.1016/j.chieco.2018.12.001

Huang, Y. J., Li, S. H., Xiang, X., Bu, Y., & Guo, Y. (2022). How can the combination of entrepreneurship policies activate regional innovation capability? A comparative study of Chinese provinces based on fsQCA. *Journal of Innovation& Knowledge*, *7*(3), 100227. doi:10.1016/j.jik.2022.100227

Jiao, H., Koo, C. K., & Cui, Y. (2015). Legal environment, government effectiveness and firms' innovation in China: Examining the moderating influence of government ownership. *Technological Forecasting and Social Change*, *96*, 15–24. doi:10.1016/j.techfore.2015.01.008

Jin, C., Xu, A., Zhu, Y., & Li, J. (2023). Technology growth in the digital age: Evidence from China. *Technological Forecasting and Social Change*, *187*, 187. doi:10.1016/j.techfore.2022.122221

Jonas, S., Nadine, K., & Solomon, D. (2021). Digital entrepreneurship in developing countries: The role of institutional voids. *Technological Forecasting and Social Change*, 170.

Lazzarini, S. G. (2015). Strategizing by the government: Can industrial policy create firm-level competitive advantage? *Strategic Management Journal*, *36*(1), 97–112. doi:10.1002/smj.2204

Leong, C., Pan, S. L., Newell, S., & Cui, L. (2016). The Emergence of self-organizing e-commerce ecosystems in remote villages of China: A tale of digital empowerment for rural development. *Management Information Systems Quarterly*, *40*(2), 475–484. doi:10.25300/MISQ/2016/40.2.11

Li, J., Xia, J., & Zajac, E. J. (2018). On the duality of political and economic stakeholder influence on firm innovation performance: Theory and evidence from Chinese firms. *Strategic Management Journal*, *39*(1), 193–216. doi:10.1002/smj.2697

Li, P. (2016). Pathways and influencing factors for improving total factor productivity: A review and analysis from the perspectives of growth accounting and frontier decomposition. *Journal of Management World*, *9*, 1–11.

Lian, X., Mu, Y. Y., & Zhang, W. Y. (2023). Digital inclusive financial services and rural income: Evidence from China's major grain-producing regions. *Finance Research Letters*, *53*, 53. doi:10.1016/j.frl.2022.103622

Liu, M., Min, S., Ma, W., & Liu, T. (2021). The adoption and impact of e-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106–116. doi:10.1016/j.jrurstud.2021.02.021

Liu, Z., & Ling, Y. (2020). Structural transformation, TFP and high-quality development. *Journal of Management World*, *36*(7), 15–29.

Mao, J., Xie, J., Hu, Z., Deng, L., Wu, H., & Hao, Y. (2023). Sustainable development through green innovation and resource allocation in cities: Evidence from machine learning. *Sustainable Development (Bradford)*, *31*(4), 1–16. doi:10.1002/sd.2516

Martinsons, M. G. (2008). Relationship-based e-commerce: Theory and evidence from China. *Information Systems Journal*, *18*(4), 331–356. doi:10.1111/j.1365-2575.2008.00302.x

Miles, M. P., & Morrison, M. (2020). An effectual leadership perspective for developing rural entrepreneurial ecosystems. *Small Business Economics*, *54*(4), 933–949. doi:10.1007/s11187-018-0128-z

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, *43*(1), 255–282. doi:10.1177/0149206316679252

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, *41*(6), 1–27. doi:10.1111/etap.12254

Peredo, A. M., & Chrisman, J. J. (2006). Toward a theory of community-based enterprise. *Academy of Management Review*, *31*(2), 309–328. doi:10.5465/amr.2006.20208683

Qiu, Z. X., & Zhou, Y. H. (2021). The mechanism of the role of e-commerce in increasing rural household income: An analysis based on a micro empirical test of the interaction between demand and supply. *Zhongguo Nongcun Jingji*, *4*, 36–52.

Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press.

Ragin, C. C. (2008). *Redesigning social inquiry*. Chicago University Press. doi:10.7208/chicago/9780226702797.001.0001

Rihoux, B., & Ragin, C. C. (2009). Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques. SAGE Publications, 1-51.

Rivera, M., Knickel, K., María Díaz-Puente, J., & Afonso, A. (2019). The role of social capital in agricultural and rural development: Lessons learnt from case studies in seven countries. *Sociologia Ruralis*, *59*(1), 66–91. doi:10.1111/soru.12218

Roberts, E., Anderson, B. A., Skerratt, S., & Farrington, J. (2017). A review of the rural-digital policy agenda from a community resilience perspective. *Journal of Rural Studies*, *54*, 372–385. doi:10.1016/j.jrurstud.2016.03.001

Schumpeter, J. A. (1912). *The theory of economic development*. Harvard University Press.

Scuotto, V., Tzanidis, T., Usai, A., & Quaglia, R. (2023). The digital humanism era triggered by individual creativity. *Journal of Business Research*, *158*, 158. doi:10.1016/j.jbusres.2023.113709

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312–320. doi:10.2307/1926047

Song, A. K. (2019). The digital entrepreneurial ecosystem—A critique and reconfiguration. *Small Business Economics*, *53*(3), 53. doi:10.1007/s11187-019-00232-y

Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice*, *41*(1), 49–72. doi:10.1111/etap.12167

Srivastava, S. C., & Shainesh, G. (2015). Bridging the service divide through digitally enabled service innovations: Evidence from Indian healthcare service providers. *Management Information Systems Quarterly*, *39*(1), 245–267. doi:10.25300/MISQ/2015/39.1.11

Stam, E., & Van de Ven, A. (2019). Entrepreneurial ecosystem elements. *Small Business Economics*.

Sussan, F., & Acs, Z. J. (2017). The digital entrepreneurial ecosystem. *Small Business Economics*, *49*(5), 1–19.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498–509. doi:10.1016/S0377-2217(99)00407-5

Tong, D., Wu, Y., & Zhu, J. et al.. (2021). The role of social capital in the collective-led development of urbanizing villages in China: The case of Shenzhen. *Urban Studies (Edinburgh, Scotland)*, *58*(16), 3335–3353. doi:10.1177/0042098021993353

Torres, P., & Godinho, P. (2021). Levels of necessity of entrepreneurial ecosystems elements. *Small Business Economics*, *59*(1), 29–45. doi:10.1007/s11187-021-00515-3

Tuukka, M., Jens, H., Sigrid, D., & Mari, W. (2023). Digital innovation's contribution to sustainability transitions. *Technology in Society*, 73.

Vaio, A. D., Palladino, R., Pezzi, A., & Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of Business Research*, *123*, 220–231. doi:10.1016/j.jbusres.2020.09.042

Wang, X. C., Li, Y., Tian, L., & Hou, Y. (2023). Government digital initiatives and firm digital innovation: Evidence from China. *Technovation*, *119*, 119. doi:10.1016/j.technovation.2022.102545

Wu, Z., Anqi, W., Yun, C., & Wei, L. (2021). Investigating inclusive entrepreneurial ecosystem through the lens of bottom of the pyramid (BOP) theory: Case study of Taobao village in China. *Chinese Management Studies*.

Yang, L., Wang, J., Feng, Y., & Wu, Q. (2022). The impact of the regional differentiation of land supply on total factor productivity in China: From the perspective of total factor productivity decomposition. *Land (Basel)*, *11*(10), 1859. doi:10.3390/land11101859

Zhang, L., Tao, Y., & Nie, C. (2022). Does broadband infrastructure boost firm productivity? Evidence from a quasi-natural experiment in China. *Finance Research Letters*, *48*, 48. doi:10.1016/j.frl.2022.102886

Zhang, M., & Du, Y. (2019). Qualitative comparative analysis (QCA) in management and organization research: Position, tactics, and directions. *Guanli Xuebao*, *16*(9), 1312–1323.

Zheng, J., Bigsten, A., & Hu, A. (2009). Can China's growth be sustained? A productivity perspective. *World Development*, *37*(4), 874–888. doi:10.1016/j.worlddev.2008.07.008

Zhou, X., Chen, T., & Zhang, B. (2023). Achieving high-quality development necessitates promoting quality, efficiency, and momentum reforms, with an emphasis on improving TFP as the core indicator and essential marker. *Land (Basel)*, *12*(1), 195. doi:10.3390/land12010195

Zhu, X., Lin, X., & Wang, T. (2020). Dynamic evolution mechanism of digital entrepreneurial ecosystem: Based on the case study of Hangzhou Yunqi town. *Guanli Xuebao*, *17*(4), 487–487.

ENDNOTE

[1] A Taobao village is a rural e-commerce hub in China where numerous small-scale entrepreneurs leverage the power of the Internet and the popular online marketplace Taobao to transform their local economies and bridge the urban–rural gap.

Xiaotong Liu is a distinguished professor at the School of Business, Qingdao University. His research topics include digital innovation and entrepreneurship, rural entrepreneurship.

Chengshuang Qi is a PhD candidate at Shanghai University of Finance and Economics. Her research focuses on digital innovation and entrepreneurship.

Yu Liu is a Master candidate in Business Administration with the Department of Gansu University of Political Science and Law. His research interests include rural revitalization and high-quality development.

Yuhuan Xia is an associate professor at SDU-SIE. His study was focused on organizational behavior and human resource management.

Haili Wu is a researcher at University College London's Centre for the Study of Decision-Making Uncertainty. She is also an associate professor at Xi'an Jiaotong-Liverpool University. Her study focuses on behavioural science.