Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-025-05398-3 OPEN

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# How digital economy and green and low carbon policies affect non-agricultural employment?—Evidence from China

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Amid the parallel advancement of green transition and digitalization, the joint mechanisms by which digital economy development and green low-carbon policies promote non-agricultural employment (NAE) remain insufficiently examined. This study introduces a "configurational–marginal" mixed analytical framework, using panel data from Chinese counties (2014–2023). By combining fuzzy-set Qualitative Comparative Analysis (fsQCA) and Multiple Linear Regression (MLR), the analysis addresses a significant research gap by uncovering both the configuration paths and marginal effects of digital and green policy tools on NAE. Findings reveal that digital infrastructure and green policies generate both "bottleneck" and "amplification" effects. Internet penetration, e-commerce platform diffusion, agricultural IoT adoption, and digital platform engagement all contribute significantly to NAE growth. In contrast, green agricultural support and low-carbon technology policies show short-term negative impacts, reflecting transitional job displacement caused by ecological upgrading and technological substitution. Policy recommendations include integrating carbon trading mechanisms and fiscal subsidies into digital platforms to magnify employment multipliers. In areas with underdeveloped digital or green capacities, addressing foundational gaps should precede coordinated investments, supported by a "digital + green" vocational training fund to alleviate structural unemployment. These findings provide practical guidance for advancing inclusive and sustainable rural employment transitions.

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## Introduction

As the global economy undergoes concurrent transitions toward digitalization and green, low-carbon development, the digital economy and green policy instruments have emerged as pivotal forces reshaping rural labor markets. In China, rural regions have long faced structural constraints such as limited industrial diversity and insufficient employment opportunities, making the supply of non-agricultural employment (NAE) particularly inadequate to meet rising demand (Wei and Jian, 2024). NAE is not only a crucial channel for increasing household income, but also a key driver of urban–rural structural optimization, labor productivity improvement in agriculture, and broader industrial upgrading (Li and Luo, 2010; Balezentis et al., 2021). Against the backdrop of simultaneous digital and green transitions, examining the synergistic impacts of the digital economy and green low-carbon policies on NAE is of considerable theoretical and practical significance for promoting equitable income distribution and sustainable development.

The digital economy—through e-commerce, digital finance, big data, and artificial intelligence—has helped overcome geographic constraints, substantially expanding rural employment boundaries (Yuan et al., 2024). While consumer-oriented digital platforms and digital financial tools have created employment opportunities for low-skilled workers, industrial internet applications and smart manufacturing have increased demand for high-skilled labor (Hu and Jia, 2025). In parallel, green low-carbon policies, via tools such as agricultural subsidies, renewable energy incentives, and eco-tourism support, are directing rural economies toward greener sectors and offering sustainable NAE pathways. The cases of "E-commerce entering villages" in Zhejiang and distributed photovoltaics in Jiangxi indicate that the synergy between digital technology and green policies can significantly enhance the local NAE level (Li and Qin, 2022; Qiu et al., 2024). However, disparities in digital infrastructure, mismatches in labor skills, and the underdevelopment of green industry markets collectively contribute to pronounced regional variations in both the quality and quantity of NAE (Zhang and Li, 2024).

Most existing studies employ variable-centered methods such as linear regression to separately examine the impact of either the digital economy or green policies on employment, making it difficult to capture the complex outcomes arising from multi-factor interactions and contextual heterogeneity (Balezentis et al., 2021). In the context of rural China, the interplay among digital technology types, policy instruments, regional development stages, and labor skill structures has led to multiple employment pathways characterized by "equifinality" (different causes, same outcome) and "multifinality" (same cause, different outcomes). However, prior research has yet to systematically explore how digital–green interactions jointly shape the configurational effects on non-agricultural employment (NAE). This gap underscores the need for an analytical approach capable of identifying complex causal relationships and context-specific pathways to deepen our understanding of NAE dynamics in rural China.

In response, this study applies fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify multiple configuration pathways through which digital economy development and green low-carbon policies interact across diverse rural settings, and to uncover their differentiated mechanisms. Specifically, the study aims to address the following questions: (1) Which combinations of digital economy indicators (DEI) and green low-carbon policy indicators (GLPI) effectively promote NAE? (2) How do these effective pathways vary across different stages of regional development and policy environments? (3) How can context-specific skill training and policy support strategies be formulated accordingly? By revealing these diverse causal mechanisms, this research seeks to provide theoretical insights and practical guidance for regionally differentiated green transitions and digitally empowered employment strategies, while contributing to the configurational analysis paradigm in DEI–GLPI interaction research.

To answer these questions, the remainder of the paper is structured as follows: Section "Literature Review" presents a literature review related to this study. Section "Research Methodology" introduces the theoretical background. Section "Indicator Design and Data Sources" employs fsQCA to identify the mechanisms through which DEI and GLPI jointly promote NAE under various rural conditions. Section "Configurational Path Analysis Based on fsQCA" conducts multiple linear regression (MLR) to quantify the strength of individual factors, assess the synergistic effect and scope of DEI–GLPI interactions, and provide a dual evidence base for targeted regional policy interventions. Section "Validation via Multiple Linear Regression" concludes with research findings and policy recommendations.

## Literature review

This study conducted a systematic literature search across databases including Web of Science, Scopus, SpringerLink, ScienceDirect, IEEE Xplore, JSTOR, and ProQuest. The keyword combination used was: ("digital economy" OR "green low-carbon policy") AND ("agriculture" OR "employment"). The search was limited to the period from 2000 to 2024. A visual clustering of research hotspots is presented in Fig. 1.

**The impact of the digital economy on NAE**. The digital economy, driven by information and communication technologies (ICT), platform-based business models, and data-centric innovation, is profoundly transforming the structure of labor demand. Existing studies consistently find that the impact of the digital economy on employment is characterized by significant sectoral and skill-based heterogeneity. For example, consumer-oriented platforms—such as e-commerce, food delivery, and ride-sharing—have created accessible, flexible employment opportunities for rural labor through what is commonly referred to as the "consumer internet" (Shahzad et al., 2022). In contrast, the widespread adoption of artificial intelligence and the industrial internet has simultaneously displaced some low- and medium-skilled jobs while generating new demand for high-skilled positions in technical services and operations through productivity-enhancing effects (Bonfiglioli et al., 2024; Zhmud et al., 2021).

In the Chinese context, the continuous improvement of rural broadband infrastructure and the rapid expansion of digital inclusive finance have significantly increased the share of stable local employment while reducing dependence on informal and gig-based work (Han et al., 2024; Ge et al., 2022). Meanwhile, empirical evidence has also confirmed the inclusive potential of digitalization in promoting employment opportunities (Qu and Fan, 2024). At the global level, the White Paper on the Global Digital Economy (2022) reports that digital activities now account for 45% of global GDP and are growing at an annual rate of 6%, indicating significant room for rural labor to transition into non-agricultural employment.

**Green low-carbon policies and NAE**. Green low-carbon policies, by promoting the development of renewable energy, eco-tourism, and the circular economy, have become an increasingly important force driving non-agricultural employment (NAE). According to the World Energy Employment Report (2022) published by the International Energy Agency, the global green economy has generated approximately 65 million jobs, with a substantial proportion located in rural areas of emerging economies. China's

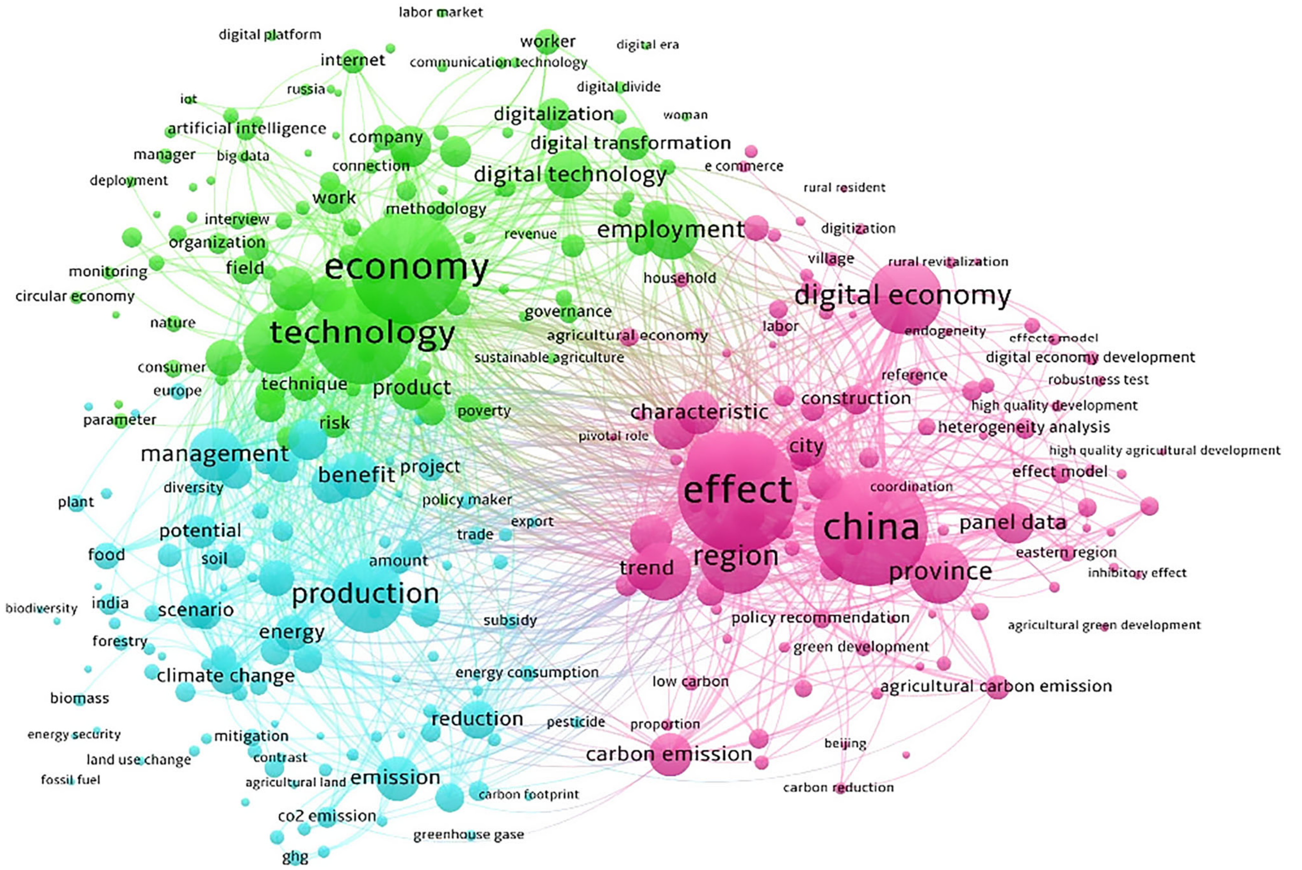


**Fig. 1** Clustered visualization of research hotspots.

experience further corroborates this trend. A joint report by the International Renewable Energy Agency and the International Labour Organization (2022) indicates that China's renewable energy sector now employs over 5.61 million people, with the share of rural employment steadily increasing.

However, the green transition is not without challenges. Countries heavily reliant on coal, such as Poland and the United Kingdom, have experienced industrial hollowing and difficulties in labor reallocation during the decarbonization process (Mayer, 2022; Jermain et al., 2024). Nevertheless, from a long-term perspective, low-carbon transitions have spurred technological innovation and industrial upgrading, thereby increasing demand for high-skilled labor (Chen et al., 2018) and ultimately contributing to net employment gains (Banacloche et al., 2022).

**Synergistic effects between the digital economy and green low-carbon policies**. Digital technologies provide robust support for green low-carbon policies in areas such as monitoring, optimization, and financing, thereby amplifying policy effectiveness. Smart grids, IoT-based energy management systems, and green finance platforms enable real-time monitoring of energy consumption, reduce transaction costs, and optimize resource allocation, significantly enhancing emission reduction outcomes (Tan et al., 2024; Wang and Shao, 2023). For instance, the "E-commerce + Green Agriculture" initiative in Zhejiang demonstrates that the integration of digital platforms with green agricultural subsidies not only expands the market for eco-friendly agricultural products but also creates a substantial number of local service jobs (Li and Zhang, 2023). Similarly, in Brazil, the coordinated development of digital agriculture and eco-tourism has opened new employment avenues for rural labor (da Silva Pinheiro et al., 2022).

From a micro-level perspective, operations management scholars have further verified the economic and employment benefits of digital–green integration. For example, hybrid energy-enabled MRP-based intelligent production systems reduce energy consumption while generating high-skilled employment opportunities (Guchhait et al., 2024); dual-channel retail strategies for green products, supported by digital platforms, expand market reach and create additional jobs (Amankou et al., 2024; Li et al., 2022). Collectively, these findings underscore the complementary relationship between the digital economy and green low-carbon policies and their multiplier effect on NAE.

**Research gap**. Based on the systematic literature search and subsequent screening of titles, abstracts, and full texts—along with backward citation tracing (snowballing)—15 studies were identified as highly relevant to this research. Table 1 summarizes the key focus areas, methodologies, and main findings of these related studies.

As shown in Table 1, existing studies tend to examine either DEI or GLPI in isolation, lacking an integrated analytical framework that explains variations in NAE through their combined influence. Moreover, linear and variable-centered models remain dominant, limiting the ability to capture complex causal mechanisms driven by multi-factor interactions and contextual heterogeneity. The fact that different combinations of digital technologies and policy instruments yield markedly divergent employment outcomes between eastern and western regions has yet to be systematically addressed in the literature, underscoring the need for a configurational perspective.

To address this gap, this study utilizes panel data from China (2014–2023) and applies fsQCA to identify multiple configurational pathways through which DEI and GLPI jointly promote NAE under varying regional conditions. Complemented by robustness-tested

**Table 1 Related Research Contributions.**

| No. | References | Methodology | Dimension of relevance | Key findings and implications |
|---|---|---|---|---|
| 1 | Deng et al. 2024 | Entropy weight method; spatial panel model; threshold model | DEI → Rural revitalization ↔ Employment | DEI shows spatial spillovers and threshold effects on rural revitalization. |
| 2 | Zhang et al. 2023 | Provincial panel regression; mediation effect; spatial analysis | DEI → Industrial integration → Employment | DEI facilitates industrial integration via innovation and human capital. |
| 3 | Jin et al. 2024 | Entropy method; spatial Durbin model; panel threshold model | DEI × Low-carbon → Carbon reduction | DEI reduces agricultural carbon emissions with regional and threshold heterogeneity. |
| 4 | Liu & Wang 2025 | CFPS microdata; IV-probit; mechanism analysis | DEI → Occupational mobility | DEI promotes rural labor shift to management and services. |
| 5 | Xiong & Sui 2025 | CLDS data; structural equation modeling; machine learning | DEI → Occupational transformation capacity | DEI strengthens occupational self-efficacy and transformation, with spillovers. |
| 6 | Han et al. 2023 | Micro survey regression; mechanism analysis | Digital application → Income & NAE | Digitalization raises income and alleviates poverty. |
| 7 | Wang et al. 2023 | Difference-in-differences-in-differences | Digital infrastructure → NAE | Broadband improves income and non-agricultural employment. |
| 8 | Zhang et al. 2024c | Panel regression; mediation & moderation effects | Energy transition policy × DEI → Revitalization | DEI magnifies employment effects of energy transition, with regional variation. |
| 9 | Liu et al. 2025 | Two-way fixed effects; mediation & threshold models | DEI → Rural economic transformation | DEI drives rural transformation through consumption upgrading; threshold effects evident. |
| 10 | Du et al. 2022 | Entropy method; coupling coordination degree; spatial econometrics | DEI ↔ Coupling with rural revitalization | Coupling between DEI and revitalization improves, but regional gaps remain. |
| 11 | Jiang et al. 2022 | Provincial panel; spatial econometrics | DEI → Agricultural green development | DEI fosters agricultural green development with spatial diffusion. |
| 12 | Zhang et al. 2024a | Extended STIRPAT model | DEI → Agricultural carbon emissions | DEI reduces emissions more effectively in high-tech investment areas. |
| 13 | Sun & Zhu 2022 | Entropy index; FE & RE regressions; nonlinear model | Digital inclusive finance → High-quality development | Digital finance supports employment and eco-performance nonlinearly. |
| 14 | Pei et al. 2024 | Spatial econometrics (SAR); robustness test | Digital inclusive finance → Poverty/employment | Digital finance reduces poverty but may cause negative spillovers. |
| 15 | Tiwasing et al. 2022 | Systematic literature review | Digital bottlenecks ↔ Rural enterprise employment | Broadband and digital training are crucial for rural enterprise job growth. |

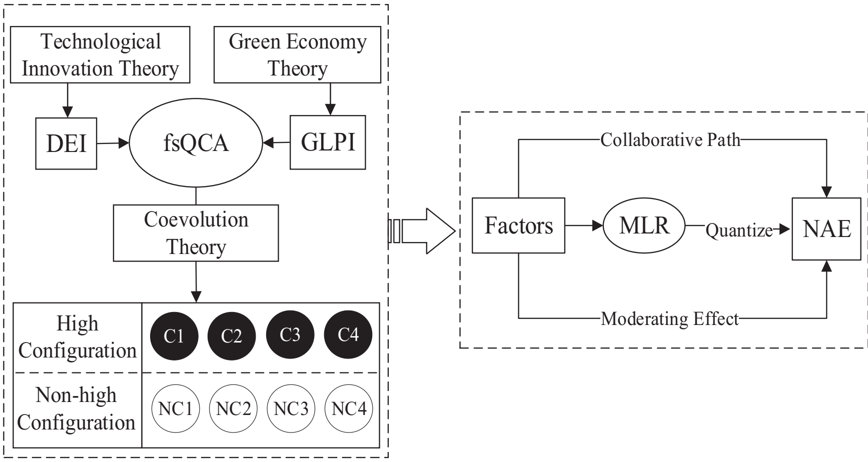


**Fig. 2** Methodological logic of fsQCA+MLR.

regression models, the marginal effects of key variables are quantified to inform differentiated policy interventions for digitally constrained areas, policy-deficient regions, and digitally green synergistic zones. By introducing a "configuration–context–outcome" analytical framework, this research seeks to explain the interaction effects and regional asymmetries overlooked in prior work, offering new theoretical insight and empirical evidence to support inclusive and sustainable rural employment transitions.

## Research methodology

This study aims to uncover how DEI and GLPI influence NAE through multiple configurational pathways. Given the inherently nonlinear, asymmetric, and context-dependent nature of this process, the additive and symmetric assumptions underlying traditional linear regression models are often untenable. By adopting a set-theoretic approach that tests both necessity and sufficiency conditions, it becomes possible to identify multiple equifinal paths—distinct combinations of causal conditions that lead to the same outcome—thus offering a more suitable analytical framework for complex socioeconomic phenomena (Pappas and Woodside, 2021). Despite its advantages, fsQCA is not without limitations. First, results can be sensitive to calibration thresholds, and subjective judgment during the calibration process may influence the findings. Second, insufficient sample size may lead to sparsity in the truth table, compromising the reliability of configurational results. Third, unlike regression analysis, fsQCA does not yield estimates of marginal effects.

To address these methodological trade-offs, this study adopts a mixed strategy of "configurational identification + marginal quantification." fsQCA is first used to identify multiple pathways through which DEI and GLPI jointly promote NAE under different contextual conditions. This is followed by MLR to assess the average marginal effects of individual conditions and their interaction terms. This integrated approach leverages fsQCA's strength in pathway discovery and MLR's capacity for marginal estimation, thereby addressing both "why" and "under what configurations" digital and green factors affect NAE, as well as "how strong" the effects are and "under what conditions" they may weaken. In doing so, the study provides a robust dual evidence base to support inclusive rural employment transitions. The methodological logic of this study is illustrated in Fig. 2.

## Indicator design and data sources

According to the theory of technological innovation, the diffusion of new technologies can reshape labor demand by enhancing productivity and transforming industrial structures (Irwin et al., 2010). Green economy theory further emphasizes that environmentally friendly technologies and industries can simultaneously foster economic growth and improve social well-being (Bowen et al., 2018). In rural contexts, these two theoretical strands are not mutually exclusive. From the perspective of coevolution theory, the interaction between technological change and policy incentives—through embeddedness and feedback mechanisms—can create path dependence and generate a cumulative employment effect over time (Li et al., 2024; Huang et al., 2022). Building on this logic, the present study constructs a DEI–GLPI–NAE analytical framework, incorporating three dimensions in indicator design: technological supply, policy provision, and market demand, in order to capture the dynamic evolution of rural employment outcomes.

Specifically, DEI contributes to GLPI by offering efficiency-enhancing tools and data infrastructure through innovations such as digital agriculture, the Internet of Things, and e-commerce platforms, thereby accelerating the development of green industries (Lajoie-O'Malley et al., 2020). Conversely, GLPI generates stable market demand and policy incentives for DEI through interventions such as green agricultural subsidies and low-carbon technology promotion (Guo, 2024). This mutual embedding enhances the resilience of rural economic systems, significantly expands NAE opportunities, and facilitates industrial upgrading and the creation of green jobs (Xu et al., 2022). Within a coevolutionary framework, DEI and GLPI thus demonstrate a mutually reinforcing relationship that jointly drives rural labor toward high value-added and sustainable employment, achieving dual goals of economic growth and environmental governance. The conceptual diagram of this framework is presented in Fig. 3.

**Indicators design and data sources of digital economy**. Technological change has profoundly influenced industrial structures and employment patterns, with DEI-driven innovation emerging as a central force in rural economic transformation (Irwin et al., 2010). Existing research shows that DEI facilitates industrial upgrading, creates new employment opportunities, improves labor productivity, and enhances job quality (Gao et al., 2024), while also promoting digital integration between agricultural and non-agricultural sectors (Lu and Huan, 2022).

The mechanisms of DEI's influence can be categorized into four dimensions. First, internet penetration reduces information barriers and enables rural labor to access digital labor markets through e-commerce and remote work (Chen et al., 2024), with penetration rates directly affecting the frequency of digital tool usage (Phan, 2023). Second, e-commerce platforms restructure agricultural product distribution systems, generating new roles in sales, logistics, and customer service (Li et al., 2024) and contributing to diversified employment forms (Tang and Zhu, 2020). Third, agricultural IoT—through the use of sensors and data analytics—improves productivity and creates technical jobs such as equipment maintenance and digital advisory services (Khanna and Kaur, 2023; Scur et al., 2023), accelerating the shift toward technology-intensive agriculture (Ullo and Sinha, 2021). Finally, digital platforms optimize resource allocation and support flexible work such as online customer support and content creation (Wang et al., 2023), enhancing employment flexibility and adaptability (Leng, 2022).

Based on these mechanisms, four indicators are constructed to capture the digital economy dimension, as detailed in Table 2.

**Indicator design and data sources of green low-carbon policy**. Green economy theory advocates for the coordinated advancement of economic growth and ecological protection through the development of environmentally friendly industries and low-carbon technological innovation. In rural areas, GLPI promotes NAE via three main pathways: (1) Green agricultural support policies (e.g., organic subsidies and clean energy projects) facilitate the transformation of traditional agriculture into new sectors such as ecological restoration and green technology extension (Unay-Gailhard and Bojnec, 2019); (2) Low-carbon technology applications (e.g., solar and wind power) generate technical jobs in equipment maintenance and carbon monitoring (Fragkos and Paroussos, 2018); and (3) Carbon emission trading policies stimulate the development of green finance and compliance-related services (Zhang and Zhang, 2020). The strength of policy enforcement directly affects the diffusion speed of green industries, with stronger enforcement accelerating labor shifts toward high value-added sectors such as green construction and eco-tourism (Jänicke, 2012).

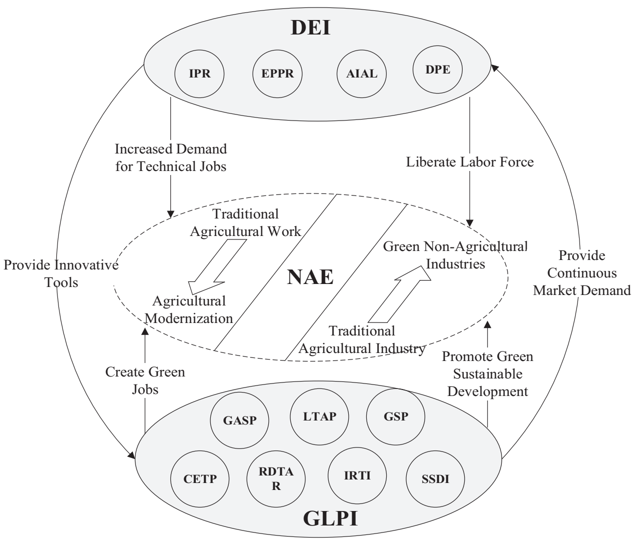


**Fig. 3** Conceptual diagram.

These effects are also reflected in structural dynamics. The Industrial Restructuring Transition Index—measured as the ratio of value added in the tertiary sector to that in the secondary sector—indicates labor movement toward green services (Huang et al., 2024), while the Service Sector Development Index—measured by annual growth rate—captures the expansion of emerging employment in areas such as eco-tourism and environmental consulting (Yang et al., 2021).

Based on the above analysis, this study constructs seven GLPI-related indicators: number of green agricultural policy documents, number of low-carbon technology policies, number of green subsidy documents, number of carbon trading policies, number of rural digital demonstration counties, Industrial Restructuring Transition Index, and Service Sector Development Index. The dataset spans 2014–2023 and integrates quantified policy texts with macroeconomic indicators to capture the transmission chain from policy provision to technological diffusion and market response. The rationale and sources for these indicators are detailed in Table 3.

## Configurational path analysis based on fsQCA

Within the fsQCA framework, a “high configuration” refers to a combination of conditions that is sufficient to trigger the desired outcome. In contrast, a “non-high configuration” does not represent random failure, but rather a systematically structured set of conditions that fail to achieve a high outcome. These configurations reveal critical bottlenecks and blocking mechanisms that constrain the improvement of NAE. From both policy and theoretical perspectives, examining high and non-high configurations in parallel offers complementary insights. High configurations identify “what combinations work,” while non-high configurations highlight “what missing elements lead to failure.” The integration of both perspectives allows policymakers to formulate holistic intervention strategies that simultaneously promote enabling factors and address structural deficiencies.

Furthermore, counties with unique geographic or economic characteristics—though underrepresented in the overall sample—often fall into non-high configurations. Ignoring these low-frequency but contextually significant paths would likely result in misaligned resource allocation. Therefore, this study adopts a dual analytical lens, conducting an in-depth analysis of both high and non-high configurations.

**Necessity analysis**. Using fsQCA software, a necessity analysis was conducted for each individual antecedent condition. A condition is considered necessary if its consistency score exceeds 0.9. As shown in Table 4, no single condition exhibits a consistency above this threshold for either the NAE population or the agricultural employment population. This suggests that no individual

**Table 2 DEI indicator construction.**

| Indicators | Theoretical Dimension | Data Sources | References |
|---|---|---|---|
| Internet Penetration Rate (IPR) | Access Conditions | *Main Indicators of Telecommunications*, National Bureau of Statistics | Chen et al. (2024); Huang et al. (2024); Phan (2023) |
| E-commerce Platform Penetration Rate (EPPR) | Application Depth | *Decade Review: 2012–2022 China E-commerce Development Data Report* | Chen et al. (2024); Li et al. (2024); Tang & Zhu (2020) |
| Agricultural IoT Adoption Level (AIAL) | Technological Integration | *Agricultural S&T Progress Contribution Rate*, Ministry of Agriculture | Chen et al. (2024); Ecer et al. (2023); Khanna & Kaur (2023); Scur et al. (2023) |
| Digital Platform Engagement (DPE) | Diffusion Scale | *China E-commerce Report (2022)*, Ministry of Commerce | Leng (2022); Wang et al. (2023) |

**Table 3 GLPI indicator construction.**

| Indicators | Theoretical dimension | Data sources | References |
|---|---|---|---|
| Green Agricultural Support Policy (GASP) | Policy Provision | Policy Database, Ministry of Agriculture | Katoch et al. (2024); Zhang et al. (2024) |
| Low-carbon Technology Application Policy (LTAP) | Technology Implementation | Policy Database, National Development and Reform Commission | Luo et al. (2024); Unay-Gailhard & Bojnec (2019) |
| Green Subsidy Policy (GSP) | Policy Provision | Policy Database, National Development and Reform Commission | Fan et al. (2023); Zhan et al. (2025) |
| Carbon Emission Trading Policy (CETP) | Market Response | NDRC Policy Database & Shanghai Environment and Energy Exchange | Zhang & Zhang (2020); Du et al. (2024) |
| Rural Digital Technology Adoption Rate (RDTAR) | Technology Implementation | E-commerce Demonstration Counties, Ministry of Commerce | Ji et al., (2023); Qiu et al., (2024) |
| Industrial Restructuring Transition Index (IRTI) | Market Response | Value Added of Tertiary and Secondary Industries, NBS | Huang et al. (2024); Lu et al., (2024) |
| Service Sector Development Index (SSDI) | Market Response | NBS – Service Production Index | Du et al., (2023), Yang et al., (2023) |

**Table 4 Necessity analysis of antecedent conditions.**

| Antecedent condition | Non-agricultural Employment | | Agricultural employment | |
|---|---|---|---|---|
| | Consistency | Coverage | Consistency | Coverage |
| IPR | 0.80597 | 0.86747 | 0.381465 | 0.355422 |
| N-IPR | 0.401119 | 0.428287 | 0.857758 | 0.792829 |
| EPPR | 0.80597 | 0.869215 | 0.411638 | 0.384306 |
| N-EPPR | 0.429105 | 0.457256 | 0.859914 | 0.79324 |
| AIAL | 0.80597 | 0.86747 | 0.390086 | 0.363454 |
| N-AIAL | 0.408582 | 0.436255 | 0.857758 | 0.792829 |
| DPE | 0.837687 | 0.875244 | 0.428879 | 0.387914 |
| N-DPE | 0.414179 | 0.455852 | 0.862069 | 0.821355 |
| GASP | 0.677239 | 0.78199 | 0.521983 | 0.521758 |
| N-GASP | 0.585821 | 0.586039 | 0.781897 | 0.677118 |
| LTAP | 0.557836 | 0.574668 | 0.701077 | 0.625216 |
| N-LTAP | 0.636194 | 0.710861 | 0.52306 | 0.505941 |
| GSP | 0.488806 | 0.564655 | 0.650862 | 0.650862 |
| N-GSP | 0.697761 | 0.697761 | 0.564655 | 0.488806 |
| CETP | 0.600933 | 0.631197 | 0.655603 | 0.59612 |
| N-CETP | 0.615485 | 0.673678 | 0.594396 | 0.563202 |
| RDTAR | 0.587687 | 0.628743 | 0.573276 | 0.530938 |
| N-RDTAR | 0.561567 | 0.603206 | 0.599138 | 0.557114 |
| IRTI | 0.505597 | 0.620137 | 0.698276 | 0.741419 |
| N-IRTI | 0.789179 | 0.751332 | 0.642241 | 0.529307 |
| SSDI | 0.722015 | 0.837662 | 0.329741 | 0.331169 |
| N-SSDI | 0.423507 | 0.421933 | 0.838362 | 0.723048 |

**Table 5 Configurational pathways for NAE.**

| Antecedent Condition | Non-Agricultural Employment | | | |
|---|---|---|---|---|
| | C1 | C2 | C3 | C4 |
| IPR | ○ | ○ | × | ○ |
| EPPR | ○ | ○ | × | ○ |
| AIAL | ● | ● | × | ○ |
| DPE | ○ | ○ | × | ○ |
| GASP | ○ | ○ | × | × |
| LTAP | ○ | × | × | × |
| GSP | × | ○ | ○ | × |
| CETP | ○ | × | ○ | × |
| RDTAR | × | ● | ● | ● |
| IRTI | | ⊗ | ⊗ | ⊗ |
| SSDI | ● | ● | ○ | × |
| Raw Coverage | 0.313433 | 0.244403 | 0.1625 | 0.199627 |
| Unique Coverage | 0.240672 | 0.104478 | 0.0337687 | 0.100746 |
| Consistency | 0.994083 | 0.992424 | 0.988649 | 0.990741 |
| Solution Coverage | 0.627052 | | | |
| Solution Consistency | 0.997034 | | | |

Note: ● indicates the presence of a core condition, ○ indicates the presence of a peripheral condition, ⊗ indicates the absence of a core condition, × indicates the absence of a peripheral condition, and blank spaces denote irrelevant conditions.

condition alone exerts a deterministic influence on employment outcomes; instead, causal relationships must be understood through specific combinations of conditions that form distinct configurational pathways.

**High-configuration pathway analysis**. By setting the case frequency threshold to 1, and using a PRI consistency threshold of 0.75 and a raw consistency threshold of 0.8, the outcome variable was manually calibrated into binary values (0 and 1). Based on this, complex, parsimonious, and intermediate solutions were obtained. Conditions that appear in both the parsimonious and intermediate solutions are identified as core conditions, whereas those present only in the intermediate solution are considered peripheral conditions. As shown in Table 5, four high-result configurations were generated, with an overall consistency of 0.997034 and a total coverage of 62.7%. These values indicate that the consistency of the configurations meets the analytical standards of fsQCA.The high-result pathways generated by fsQCA can be categorized into four distinct mechanisms through which DEI and GLPI jointly promote NAE.

(1) Digitally Empowered Model (C1)
This configuration highlights the critical role of robust digital infrastructure and a supportive service sector. With a configuration consistency of 0.994083, it accounts for approximately 31.3% of NAE cases. When digital elements are fully developed and green policies such as LTAP and CETP are effectively aligned, NAE can be significantly enhanced even in the absence of broad-based green subsidies (~GSP). This pathway is particularly applicable to economically advanced eastern coastal regions such as Zhejiang, Jiangsu, and Guangdong, where digital infrastructure is well-established, e-commerce platforms are highly developed, and agricultural IoT applications are increasingly widespread. GASP and LTAP are also well implemented in these areas.

**Table 6 Agricultural employment population configuration path.**

| Antecedent Condition | Agricultural employment population | | | |
|---|---|---|---|---|
| | NC1 | NC2 | NC3 | NC4 |
| IPR | × | × | × | ○ |
| EPPR | ⊗ | ⊗ | ⊗ | ○ |
| AIAL | ⊗ | ⊗ | ⊗ | ○ |
| DPE | × | × | × | ○ |
| GASP | × | ○ | ○ | ○ |
| LTAP | ● | ● | ● | ○ |
| GSP | | ○ | ○ | × |
| CETP | ● | ● | × | ○ |
| RDTAR | × | ○ | ○ | × |
| IRTI | ○ | ○ | ○ | × |
| SSDI | ⊗ | ⊗ | ○ | × |
| Raw Coverage | 0.306465 | 0.18556 | 0.189871 | 0.209052 |
| Unique Coverage | 0.198707 | 0.0778017 | 0.101509 | 0.122845 |
| Consistency | 1 | 1 | 1 | 1 |
| Solution Coverage | 0.610776 | | | |
| Solution Consistency | 1 | | | |

Note: ● indicates the presence of a core condition, ○ indicates the presence of a peripheral condition, ⊗ indicates the absence of a core condition, × indicates the absence of a peripheral condition, and blank spaces denote irrelevant conditions.

For instance, Zhejiang's "Digital Villages" initiative and its cluster of "Taobao Villages" exemplify this configuration: nearly full county-level broadband coverage, high platform penetration, and widespread adoption of agricultural IoT technologies are complemented by smart farming projects driven by LTAP and green manufacturing initiatives incentivized by CETP. Together, these factors have led to the creation of numerous new employment opportunities in e-commerce, logistics, and digital agricultural services, fully aligning with the condition structure of C1 and affirming the explanatory power of the model in developed eastern regions.

(2) Resource-Dependent Model (C2)
This configuration demonstrates a consistency score of 0.992424 and accounts for approximately 24.4% of NAE cases. In contexts where IRTI is lagging and carbon market mechanisms are absent (~CETP), alternative employment growth can be achieved through GSP and RDTAR. This pathway is characteristic of economically underdeveloped or industrially weak regions, particularly in parts of central and western China, such as rural counties in Gansu, Guizhou, and Yunnan provinces. In these areas, delayed industrial restructuring has hindered the generation of adequate employment opportunities through traditional upgrading strategies. As a result, local economies rely more heavily on existing resources—namely policy support, digital applications, and basic infrastructure—to generate substitute forms of NAE.
For example, in some areas of Yunnan Province, the promotion of agricultural IoT and increased engagement with digital platforms have expanded market access for regional specialty products such as Pu'er tea and fresh flowers. Although advanced service sectors have yet to emerge, non-agricultural employment opportunities in packaging, logistics, and online customer service have grown considerably, reflecting the core mechanism of configuration C2.

(3) Multi-Policy Synergy Model (C3)
In remote western counties with weak digital infrastructure, GSP and CETP to coordinate resources through top-down intervention. At the same time, improvements in RDTAR help increase rural residents' adoption of basic digital technologies, compensating for limited market mechanisms and generating employment in ecological protection and green project implementation. This configuration is particularly applicable to remote western regions and some nationally designated poverty-stricken counties, such as those in Qinghai Province, Ningxia Hui Autonomous Region, and parts of the Xinjiang Uygur Autonomous Region. These areas commonly face challenges such as low levels of marketization, inadequate infrastructure, and slow industrial upgrading, making it difficult to stimulate NAE growth through market forces alone.
Government-led initiatives—such as the implementation of green subsidy policies and carbon emission trading mechanisms—have accelerated the integration of resources and expansion of employment opportunities. For instance, ecological restoration projects in Hainan Prefecture, Qinghai, have created positions such as forest rangers and monitoring personnel, directly reflecting the top-down, policy-driven nature of configuration C3. In addition, the rollout of carbon trading policies has attracted enterprise participation in green and low-carbon industries, providing new momentum for regional economic development. This configuration has a consistency score of 0.98865 and accounts for approximately 16.25% of NAE cases.

(4) Digital Technology-Driven Model (C4)
Configuration C4 is primarily driven by widespread internet access and a robust platform economy. In contexts where formal policy support is relatively limited, this pathway facilitates labor absorption through flexible employment opportunities such as e-commerce entrepreneurship and digital content creation. The consistency score for this configuration is 0.98865, accounting for ~16.25% of NAE cases.
This model is particularly applicable to economically advanced regions with strong DEI foundations, such as Zhejiang, Jiangsu, and Fujian provinces. For instance, the "rural livestream e-commerce" phenomenon observed in cities like Quanzhou and Jinjiang in Fujian exemplifies this pathway: local farmers sell aquatic products and tea through livestreaming platforms supported by well-developed logistics infrastructure. Even in the absence of deep industrial upgrading or a mature service sector, digital technologies alone have emerged as the primary driver of employment growth. Moreover, high levels of RDTAR in these regions have improved rural residents' familiarity with and acceptance of digital tools, thereby further accelerating the expansion of digitally driven NAE.

**Analysis of non-high configurations**. Non-high configuration analysis identifies secondary or marginal pathways that, under specific conditions or within localized contexts, exert significant influence on the outcome variable. These configurations serve as a supplement to high-result pathways by capturing cases that are otherwise unaccounted for. In the domains of policymaking, resource allocation, and regional development, such low-frequency configurations may reflect the unique characteristics and needs of particular areas or population groups. To more comprehensively capture the complex interactions among variables and avoid overly one-sided conclusions, this study further conducts a non-high configuration analysis. Based on empirical

**Table 7 Regression Model 1 (Control Variable: IPR).**

| | Unstandardized coefficient | | Standardized coefficient | $t$ | Significance | Collinearity statistics | |
|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | Tolerance | VIF |
| (constant) | 0.298 | 0.066 | | 4.534 | 0.011 | | |
| IPR | 1.135 | 0.106 | 1.336 | 10.723 | 0 | 0.257 | 3.884 |
| GASP | −0.388 | 0.116 | −0.392 | −3.354 | 0.028 | 0.293 | 3.412 |
| LTAP | −0.61 | 0.081 | −0.576 | −7.508 | 0.002 | 0.679 | 1.473 |
| GSP | 0.317 | 0.089 | 0.347 | 3.575 | 0.023 | 0.424 | 2.358 |
| CETP | 0.224 | 0.062 | 0.284 | 3.601 | 0.023 | 0.644 | 1.554 |
| $R^2$ | 0.984 | | | | | | |
| Adjust $R^2$ | 0.964 | | | | | | |
| $F$ | 49.229 | | | | | | |

results, four distinct non-high configuration types are identified, as shown in Table 6.

(1) Digitally Deficient Model (NC1)
This configuration is characterized by the absence of all key digital elements—such as internet infrastructure, platforms, e-commerce, and IoT—as well as an underdeveloped service sector. Even with the presence of LTAP and CETP, these factors are insufficient to stimulate employment growth. NC1 accounts for 30.6% of non-high outcome cases and is primarily concentrated in high-altitude counties across Qinghai, Tibet, and parts of southwestern China. For example, in Zhiduo County, Yushu Prefecture, Qinghai Province, the household fiber-optic coverage rate was below 40% in 2022, with only one small courier outlet in operation. Moreover, over 85% of workers in local green infrastructure projects were non-local, indicating that local laborers were largely excluded—underscoring the employment-constraining effect of digital infrastructure deficiencies.

(2) Service–Digital Decoupling Model (NC2)
Compared to NC1, NC2 features a relatively higher RDTAR, but still lacks sufficient development in the service sector, breaking the chain of synergy between digital tools and service-driven employment. This configuration covers 18.6% of the sample, with representative cases found in Ningxia Hui Autonomous Region, Gansu Province, and other inland northwestern areas. Although these regions have implemented rural e-commerce demonstration county programs, the share of services in local GDP remained below 50% in 2024. As a result, online transactions have failed to translate into significant job creation due to limited local logistics and after-sales service capacity.

(3) Technological and Carbon Policy Deficiency Model (NC3)
NC3 reveals a "dual constraint" stemming from weak digital infrastructure and the absence of carbon trading mechanisms. Although green agricultural support and low-carbon technology promotion are in place, the lack of carbon market price signals weakens investment incentives, limiting the potential for green-driven transformation in the service and manufacturing sectors. This configuration explains 19.0% of cases, predominantly in economically underdeveloped counties in Hunan and Jiangxi provinces. For instance, in Shicheng County, Jiangxi, the installed capacity of poverty alleviation solar projects ranks among the highest in the province. However, carbon quota allocations have not yet extended to the county level, constraining green project financing. Most new employment consists of short-term construction roles, failing to generate sustained job absorption.

(4) Digital–Service Weakness Model (NC4)
NC4 indicates that although digital infrastructure is in place, low adoption of digital technologies among rural residents, coupled with stagnant industrial upgrading and limited service sector growth, has diminished the potential of digital dividends. This configuration accounts for 21.0% of cases and is mainly observed in rural areas of Shandong and Hebei provinces. Despite express delivery coverage exceeding 95%, the year-on-year growth of value added in the tertiary sector remains below 5%, and in some cases negative. As a result, digital employment opportunities tend to spill over to nearby prefecture-level cities, with limited local retention.
Through counterfactual configuration analysis based on fsQCA, the four non-high configurations collectively reveal three blocking mechanisms. First, the structural constraint effect shows that significant deficiencies in either DEI infrastructure or GLPI intensity can lock NAE into a low-level equilibrium, affirming the structural inertia imposed by institutional shortfalls. Second, the coordination threshold mechanism highlights that isolated interventions are insufficient to overcome compound development bottlenecks. In particular, the employment multiplier effect of SSDI and DPE only becomes significant when both cross a critical threshold; below that, the system risks falling into a "policy–technology decoupling" trap. Third, geographic heterogeneity in response indicates that counties located in plateaus, hills, and plains face distinct constraints, necessitating place-based policy combinations tailored to regional conditions.

**Robustness test**. To assess the robustness of the fsQCA results, the consistency threshold was raised from 0.80 to 0.85, the PRI threshold from 0.75 to 0.80, while maintaining the frequency threshold at 1. The revised model yielded results that are broadly consistent with those of the original model. Both overall consistency and coverage exceed 0.9 and 0.5, respectively, and the identified configurations remain unchanged, confirming the robustness of the findings.

## Validation via multiple linear regression

While the fsQCA analysis identified multiple configurational pathways through which DEI and GLPI jointly influence NAE, its set-theoretic logic emphasizes the "parallel sufficiency" of different condition combinations and does not quantify the average marginal effect of each factor. To further validate and complement the fsQCA results, this study employs a MLR model to assess the overall magnitude of DEI and GLPI effects on NAE, and to explore the heterogeneous impact of various policy instruments under different levels of digital infrastructure.

The results of the first regression model (Table 7) indicate strong explanatory power ($R^2 = 0.984$, adjusted $R^2 = 0.964$; $F = 49.229$, $p < 0.001$), suggesting that the included variables effectively capture county-level variation in NAE rates. The standardized coefficient of IPR is 1.336 ($t = 10.723$, $p < 0.001$), reaffirming the critical role of digital infrastructure in supporting

**Table 8 Regression Model 2 (Control Variable: EPPR).**

| | Unstandardized coefficient | | Standardized coefficient | *t* | Significance | Collinearity statistics | |
|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | Tolerance | VIF |
| (constant) | 0.157 | 0.126 | | 1.249 | 0.28 | | |
| EPPR | 1.276 | 0.204 | 1.305 | 6.259 | 0.003 | 0.253 | 3.948 |
| GASP | −0.597 | 0.222 | −0.603 | −2.689 | 0.055 | 0.219 | 4.557 |
| LTAP | −0.436 | 0.141 | −0.411 | −3.093 | 0.036 | 0.623 | 1.604 |
| GSP | 0.168 | 0.134 | 0.184 | 1.256 | 0.277 | 0.512 | 1.954 |
| CETP | 0.316 | 0.106 | 0.4 | 2.973 | 0.041 | 0.609 | 1.643 |
| $R^2$ | 0.956 | | | | | | |
| Adjust $R^2$ | 0.901 | | | | | | |
| *F* | 17.354 | | | | | | |

**Table 9 Regression Model 3 (Control Variable: AIAL).**

| | Unstandardized coefficient | | Standardized coefficient | *t* | Significance | Collinearity statistics | |
|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | Tolerance | VIF |
| (constant) | 0.218 | 0.081 | | 2.708 | 0.054 | | |
| AIAL | 1.266 | 0.135 | 1.380 | 9.369 | 0.001 | 0.239 | 4.187 |
| GASP | −0.508 | 0.142 | −0.513 | −3.577 | 0.023 | 0.252 | 3.964 |
| LTAP | −0.518 | 0.094 | −0.489 | −5.505 | 0.005 | 0.656 | 1.523 |
| GSP | 0.333 | 0.102 | 0.365 | 3.253 | 0.031 | 0.412 | 2.426 |
| CETP | 0.263 | 0.072 | 0.333 | 3.672 | 0.021 | 0.632 | 1.582 |
| $R^2$ | 0.979 | | | | | | |
| Adjust $R^2$ | 0.953 | | | | | | |
| *F* | 37.788 | | | | | | |

employment. Green policy variables exhibit clear divergence: both GSP and CETP show positive and significant effects ($\beta = 0.347$ and 0.284; $p < 0.05$), indicating that fiscal incentives and carbon market mechanisms can directly boost NAE by expanding related service-sector jobs in digitally advanced counties. In contrast, GASP and LTAP are negatively associated with NAE ($\beta = -0.392$ and $-0.576$; $p < 0.05$), suggesting that ecological restructuring and technological substitution may initially displace traditional employment, leading to short-term adjustment pressures.

All VIF values are below 4, indicating no serious multicollinearity. Overall, the regression results empirically support two key propositions: digital infrastructure gaps weaken the effectiveness of green policy incentives, while strong digital–green complementarity amplifies employment outcomes. These findings provide a robust basis for designing targeted and differentiated policy interventions.

In the second stage of empirical analysis (Table 8), EPPR was used as the sole digital control to assess the independent impact of green policies on NAE, with digital market access effectively "held constant." This approach isolates the employment effects of commercial digitalization, enabling a clearer view of how green policies interact with labor dynamics. As shown in Table 8, the model maintains strong explanatory power (adjusted $R^2 = 0.901$; $F = 17.354$; $p < 0.001$), indicating that green policies and EPPR together explain substantial variation in county-level NAE.

EPPR has a strong positive effect on NAE ($\beta = 1.305$, $p = 0.003$), reaffirming the central role of e-commerce in rural employment. However, both GASP and LTAP remain significantly negative ($\beta = -0.603$ and $-0.411$, $p < 0.10$), with greater magnitude than in the baseline model. This suggests that rapid expansion of online commerce, if not matched by production-side upgrades, may intensify the crowding-out of traditional jobs. In contrast, CETP continues to show a significant positive effect ($\beta = 0.400$, $p = 0.041$), indicating that market-based instruments can still enhance employment in a digitalized commercial setting. GSP, however, loses significance, implying that untargeted subsidies may have limited effect without integration into platform ecosystems. Multicollinearity remains within acceptable bounds (max VIF $= 4.557$). Overall, the findings highlight a potential mismatch between digital commercialization and green production upgrades. Without synchronization, early-stage digital expansion may constrain job growth; by contrast, CETP and other market-aligned instruments can help align digital and green transformations to sustain employment gains. These insights offer empirical support for phased and targeted policy design.

In the third regression model, AIAL is used as the sole control variable to evaluate whether green policies maintain their marginal impact on NAE under advanced production-side digitalization. As AIAL reflects the degree of technological integration in agricultural processes, it serves as a proxy for the digital foundation influencing labor shifts to non-agricultural sectors. Table 9 shows strong model performance (adjusted $R^2 = 0.953$; $F = 37.788$, $p < 0.001$), with acceptable multicollinearity (max VIF $= 4.187$).

AIAL exerts a strong positive effect on NAE ($\beta = 1.380$, $p = 0.001$), supporting the "technology-enabled labor release" hypothesis. Under this high-tech setting, GSP and CETP remain significantly positive ($\beta = 0.365$ and 0.333, $p < 0.05$), indicating that fiscal incentives and carbon markets can complement digitalization by generating jobs in logistics, maintenance, and carbon asset services. In contrast, GASP and LTAP continue to show significant negative effects ($\beta = -0.513$ and $-0.489$, $p < 0.05$), suggesting that ecological upgrades and technological substitution may still displace traditional labor in the short term, with longer-term employment benefits yet to emerge. Overall, the findings highlight that in high-AIAL contexts, CETP and GSP should be prioritized to maximize digital employment dividends, while GASP and LTAP require complementary reskilling and industrial transition measures to mitigate short-term displacement and achieve sustainable employment growth.

In the fourth regression model, Digital Platform Engagement (DPE) is used as the sole digital control to isolate the employment effects of the platform economy and assess the independent

**Table 10 Regression Model 4 (Control Variable: DPE).**

| | Unstandardized coefficient | | Standardized coefficient | $t$ | Significance | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | Tolerance | VIF |
| (constant) | 0.138 | 0.098 | | 1.409 | 0.232 | | |
| DPE | 1.26 | 0.152 | 1.299 | 8.266 | 0.001 | 0.266 | 3.753 |
| GASP | −0.597 | 0.169 | −0.603 | −3.528 | 0.024 | 0.225 | 4.437 |
| LTAP | −0.334 | 0.113 | −0.315 | −2.956 | 0.042 | 0.579 | 1.728 |
| GSP | 0.133 | 0.1 | 0.145 | 1.321 | 0.257 | 0.545 | 1.835 |
| CETP | 0.266 | 0.081 | 0.336 | 3.295 | 0.03 | 0.631 | 1.585 |
| $R^2$ | 0.974 | | | | | | |
| Adjust $R^2$ | 0.941 | | | | | | |
| $F$ | 29.608 | | | | | | |

impact of green policies under high platform penetration. As shown in Table 10, the model performs well (adjusted $R^2 = 0.941$; $F = 29.608$, $p < 0.001$), with DPE exerting a strong positive effect on NAE ($\beta = 1.299$, $p = 0.001$), reaffirming its importance in rural labor absorption.

Among green policy variables, CETP remains significantly positive ($\beta = 0.336$, $p = 0.030$), indicating its continued ability to generate employment in carbon asset management and green certification, even in platform-driven contexts. In contrast, GSP, while positive, becomes insignificant ($p = 0.257$), suggesting that fiscal incentives may be partially offset by platform effects in highly digitalized areas. GASP and LTAP continue to show significant negative effects, indicating that production-side ecological reforms and technology substitution still suppress traditional jobs, even amid platform expansion. Multicollinearity is within acceptable limits (max VIF = 4.437), supporting the robustness of the estimates.

Regression results from Tables 7 to 10 yield three key insights: First, CETP consistently shows a robust positive effect across all digital contexts, underscoring its broad effectiveness in green resource allocation and low-carbon employment generation. Second, the persistently negative coefficients for GASP and LTAP—despite limited variation—suggest that their employment impacts are constrained by structural transition lags and skill mismatches, requiring complementary training and industrial support to become positive. Third, the significance of GSP declines under DPE, indicating marginal substitution; without deep integration into platform ecosystems, its employment multiplier effect diminishes.

By sequentially controlling for IPR, EPPR, AIAL, and DPE, the stepwise regression isolates the marginal effects of green policies, strengthens causal interpretation, and lays a solid empirical foundation for exploring digital–green policy synergies.

## Discussion

Panel data from 2014–2023 reveal that DEI's impact on NAE follows a "fast-then-stabilize" pattern: employment elasticity peaks within the first three years of policy or capital input, then slows as the system enters platform consolidation and market segmentation. Without corresponding gains in SSDI or IRTI, digital jobs risk devolving into low value-added roles (e.g., low-wage livestreaming, basic sorting). Sustaining digital dividends thus requires not just one-time platform expansion but continuous service sector growth, industrial upgrading, and skill renewal. This highlights the need for integrated planning—aligning digital projects with industrial support and retraining—to prevent "early stagnation" and ensure DEI drives long-term employment and income gains.

**Individual and synergistic effects**. Regression results confirm that both DEI and GLPI independently contribute positively to NAE. However, their interaction term (DEI×GLPI) remains significant and has a greater marginal effect than either variable alone, indicating a clear "amplification synergy": the two are mutually reinforcing, not merely additive. Quantile regressions show this synergy depends on baseline development. When DEI is in the bottom quartile, GLPI's marginal effect vanishes; conversely, low GLPI limits the employment impact of DEI. This validates a "bottleneck effect"—without joint development, policy dividends diminish sharply. DEI without GLPI may result in "platform ineffectiveness," while GLPI without digital support risks becoming a "policy island."

An effective strategy for boosting NAE is thus a "dual-engine" approach: accelerating digital infrastructure, platform adoption, and IoT deployment, while simultaneously enhancing green subsidies, low-carbon technologies, and carbon market mechanisms. Coordinated implementation ensures the two tracks converge, maximizing employment gains through sustained synergy.

**Regional variation and historical path dependence**. The fsQCA results reveal clear regional differentiation. Eastern coastal counties typically follow a "Digitally Empowered" pathway, where high internet penetration, e-commerce platform use, and agricultural IoT adoption—combined with a mature service sector—create strong synergies that significantly boost NAE. In contrast, northwestern and southwestern counties more often reflect a "Multi-Policy Synergy" model, relying on green subsidies, carbon trading, and fragmented digital practices, with employment shifts largely government-driven.

These differences stem from two deeper structural factors: industrial history and social capital. First, many resource-based counties have long relied on primary-sector extraction, resulting in lagging SSDI and IRTI. As a result, even with digital platform access, the lack of a local service base or high–value-added industries limits their capacity to absorb digital-driven employment. Second, in coastal regions like Zhejiang and Fujian, traditional social structures—such as clan networks and local elite culture—facilitate information flow, credit assurance, and risk sharing, supporting the rapid growth of e-commerce clusters. In contrast, pastoral and remote highland areas suffer from weak social ties, making the diffusion of digital technologies more difficult due to higher trust and adoption barriers.

**Comparison of international policy experiences**. To explore global variations in NAE transformation and enhance the external relevance of this study, four representative countries—the United States, China, France, and India—are selected for comparative analysis. The United States, as a developed economy, is facing a structural slowdown in NAE growth. Its efforts to balance a shortage of high-skilled jobs with the expansion of the gig economy offer practical lessons. China demonstrates a policy-

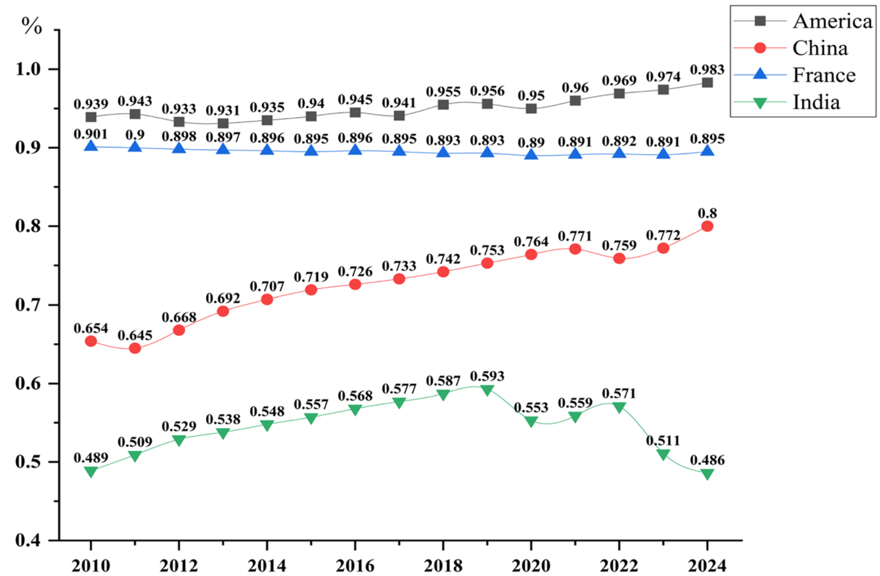


**Fig. 4** Trend chart of NAE proportion in four countries.

driven approach to green transition and NAE upgrading, revealing both achievements and institutional challenges. France, as an EU member, reflects the labor market volatility caused by ambitious green reforms. India offers insights into managing skill mismatches and rural–urban disparities under the dual expansion of digital and green employment.

These countries differ significantly in development stages, policy tools, and institutional contexts, providing a multidimensional basis for understanding how digital economy and green low-carbon policies shape NAE. To support cross-national comparison, the study calculates the share of NAE in total employment from 2010 to 2024 (Fig. 4) and links trends with key policy practices, offering internationally relevant guidance for optimizing NAE structures in Chinese counties.

In order to test the external applicability of research conclusions and provide reference experiences for policymakers and relevant stakeholders, this paper selects four representative international cases: the "Silicon Valley-Detroit" AI + automotive integration model in the United States, the "Photovoltaic + Agriculture" county pilot in China, France's "2030 Plan," and India's "Rural Employment Guarantee Scheme," to compare the non-agricultural employment practices of different countries in the context of promoting the digital economy and green transformation (Table 11).

The United States has promoted non-agricultural employment by integrating AI with the automotive industry, combining gig economy growth and tax incentives to add 228,000 NAE positions by 2025. However, recent figures show a slowdown to 152,000 monthly, revealing a widening "skills gap." In response, firms are adopting "skills monetization" tools, such as blockchain-based certifications, to convert non-degree training into recognized qualifications. China's "Photovoltaic + Agriculture" initiative pushes digital infrastructure into rural counties, coupled with government investment and employment workshops. This strategy is expected to create 3 million grassroots jobs and raise urban NAE to 75% by 2025. Yet, regional inequality persists—central and western provinces trail the east by 12 percentage points—prompting the need for interregional training centers to rebalance opportunity distribution.

France's "2030 Plan" supports SME green transitions through the hydrogen energy sector, spurring a 15% rise in regional NAE. However, high costs have slowed automation, highlighting the need for affordable skills training and labor cost adjustments. A unified EU framework for employment statistics and training is recommended. In India, the Rural Employment Guarantee Program has advanced digital growth through outsourcing and e-commerce, while green jobs remain concentrated in skill-intensive sectors. Although 350,000 solar jobs were created in 2024, land displacement pushed 200,000 agricultural workers into low-skill roles, reinforcing a shift toward gig-based NAE. To address this, India now mandates platform firms to contribute to unemployment insurance, strengthening protections for informal workers.

A comprehensive comparison of the four countries' cases shows that a sound skills training system, improved supporting infrastructure, and a follow-up social security mechanism are key supporting conditions for whether digital and green policies can be transformed into sustainable employment growth. Without these foundations, even with sufficient policy incentives, it is difficult to achieve long-term, structural employment increases.

**Stakeholder-oriented policy recommendations**. For policymakers, a "dual-track investment" strategy is recommended: prioritize funding and technical support for counties with significantly lagging DEI or GLPI until baseline thresholds are met, then advance coordinated investment in both areas. This approach mitigates the "barrel effect" of diminishing returns and resource inefficiency. Additionally, establishing a "regional vocational training fund" is essential. Counties should embed cross-cutting "digital + green" skills—such as e-commerce, photovoltaic maintenance, and carbon asset management—into local training systems, with targeted subsidies (e.g., tuition waivers, transport support) to improve access for low-income and vulnerable groups.

For rural enterprises, collaboration with local governments to build traceability and carbon footprint platforms using blockchain or IoT technologies can enhance transparency, raise green value-added, and support carbon trading. Internally, firms should establish career pathways for emerging roles like IoT maintenance and green certification, integrating them into training and performance systems to retain talent and build organizational capacity.

NGOs (non-governmental organizations) should deploy mobile training units in resource-dependent areas, offering digital literacy and low-carbon skills to underserved groups, especially

**Table 11 Comparison of international policy cases.**

| Country/region | Digital economy strategy | Green policy focus | NAE outcomes | Key challenge | Policy implication |
|---|---|---|---|---|---|
| United States (Silicon Valley-Detroit AI + Auto Integration) | E-commerce and gig economy absorbing low-skilled labor | Tax incentives for private sector green investment | 228,000 new non-agricultural jobs in 2025 | Skills gap due to shortage of high-skilled positions | Transform non-degree training outcomes into promotion credentials |
| China ("Photovoltaic + Agriculture" County Model) | County-level digital infrastructure rollout; 3 million grassroots tech jobs created | Large-scale renewable energy investment + employment-support workshops | Urban NAE share projected to reach 75% in 2025 | High local industrial concentration; regional imbalance persists | Establish interregional training centers to improve spatial equity |
| France ("France 2030" Plan) | High value-added digital economy | Green transition of SMEs | Hydrogen industry chain drives 15% growth in regional NAE | SMEs delay automation due to high costs | Promote EU-wide standardized digital job statistics |
| India (Rural Employment Guarantee Program) | Digital economy expansion (outsourcing, e-commerce) | Green jobs concentrated in tech-intensive sectors | Solar capacity created 350,000 direct jobs in 2024, but gig economy still dominates | Lack of social protection in gig economy | Mandate platform companies to contribute unemployment insurance for informal workers |

women and older workers. NGOs can also act as third-party evaluators, publishing independent assessments of green subsidy and carbon trading policy outcomes to inform government decisions and strengthen public trust.

## Conclusions

Drawing on panel data from China spanning 2014–2023, this study employs a dual-method approach combining fsQCA for configurational identification and MLR for marginal quantification to systematically examine the independent and joint effects of DEI and GLPI on NAE. The key findings are as follows:

(1) fsQCA identifies four high-performing configurations—Digitally Empowered, Resource-Dependent, Multi-Policy Synergy, and Digital Technology-Driven—as well as four non-high configurations, reflecting both "bottleneck" and "amplification" effects stemming from imbalances or synergies between digital infrastructure and green policy.

(2) Regression results show that Internet Penetration Rate, Platform Penetration Rate, Agricultural IoT Adoption Level, and Digital Platform Engagement significantly boost NAE. CETP consistently demonstrates a positive effect across models, whereas GSP is only effective in areas with low platform penetration.

(3) GASP and LTAP exhibit short-term negative impacts in all models, indicating that ecological restructuring and technological substitution may temporarily displace traditional jobs, underscoring the urgent need for reskilling and industrial transition measures.

Theoretically, this study fills a gap in the literature on the joint influence of DEI and GLPI on NAE and proposes a novel "configurational–marginal" hybrid analytical framework. Practically, it offers evidence-based guidance for differentiated digital–green policy combinations, highlighting the central role of carbon trading mechanisms and platform ecosystems in employment creation. The study emphasizes the importance of synchronizing digital infrastructure and green policy deployment; integrating carbon markets and subsidies into platform economies; and adopting a staged approach for digitally or environmentally underdeveloped regions—prioritizing shortfall correction before coordination—supplemented by "digital + green" vocational training funds.

This study has several limitations. It primarily relies on macro-level indicators, without distinguishing the impacts of specific digital technologies or accounting for cultural capital. Although fixed effects and instrumental variables were used for causal inference, unobserved biases may remain. Future research could explore the heterogeneous employment effects of GLPI across institutional and cultural settings, particularly in low-income countries. Incorporating firm- or individual-level data would help assess how technologies like blockchain-based traceability or AI quality control influence job types and wage structures. Methodologically, event studies or panel discontinuity designs could better capture pre- and post-policy employment shifts, while examining how social networks and local trust shape digital diffusion and green policy effectiveness.

## Data availability

No datasets were generated or analysed during the current study.

Received: 4 February 2025; Accepted: 20 June 2025;
Published online: 06 August 2025

## References

Amankou KAC, Guchhait R, Sarkar B, Dem H (2024) Product-specified dual-channel retail management with significant consumer service. J Retail Consum Serv 79:103788. https://doi.org/10.1016/j.jretconser.2024.103788

Balezentis T, Li T, Chen X (2021) Has agricultural labor restructuring improved agricultural labor productivity in China? A decomposition approach. Socio-econ Plann Sci, 76:100967. New York: Elsevier Science Inc. https://doi.org/10.1016/j.seps.2020.100967

Banacloche S, Lechon Y, Rodríguez-Martínez A (2022) Carbon capture penetration in Mexico's 2050 horizon: a sustainability assessment of Mexican CCS policy. Int J Greenh Gas Control 115:103603. https://doi.org/10.1016/j.ijggc.2022.103603

Bonfiglioli A., Crinò R, Gancia G, Papadakis I (2024) Artificial intelligence and jobs: evidence from US commuting zones*. Econ Policy eiae059. https://doi.org/10.1093/epolic/eiae059

Bowen A, Kuralbayeva K, Tipoe EL (2018) Characterising green employment: The impacts of 'greening' on workforce composition. Energy Econ 72: 263–275. Amsterdam: Elsevier Science Bv. https://doi.org/10.1016/j.eneco.2018.03.015

Chen F, Shi S, Chen W (2024) Internet usage and non-farm employment of rural labor: micro-survey data from rural China [J]. Soci Indic Res 1-22

Chen Q, Tsai SB, Zhai Y, Zhou J, Yu J, Chang LC, Li G, Zheng Y, Wang J (2018) An empirical study on low-carbon: human resources performance evaluation. Int J Environ Res Public Health 15(1): 62. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/ijerph15010062

Deng X, Huang M, Peng R (2024) The impact of digital economy on rural revitalization: evidence from Guangdong, China. Heliyon 10:e28216. https://doi.org/10.1016/j.heliyon.2024.e28216

Du J, Zeng M, Deng X (2024) The policy effect of carbon emissions trading on green technology innovation—evidence from manufacturing enterprises in China. Clim Change Econ 15(01): 2340006. Singapore: World Scientific Publ Co Pte Ltd. https://doi.org/10.1142/S2010007823400067

Du M, Huang Y, Dong H, Zhou X, Wang Y (2022) The measurement, sources of variation, and factors influencing the coupled and coordinated development of rural revitalization and digital economy in China. PLoS One 17:e0277910. https://doi.org/10.1371/journal.pone.0277910

Du R, Qiao J, Feng Y (2023) The impact of the agricultural productive service industry on the income gap between urban and rural residents: evidence from 276 Chinese prefecture-level cities. Singapore Econ Rev https://doi.org/10.1142/S0217590823500522

Ecer F, Ogel IY, Krishankumar R, Tirkolaee EB (2023) The q-rung fuzzy LOPCOW-VIKOR model to assess the role of unmanned aerial vehicles for precision agriculture realization in the Agri-Food 4.0 era[J]. Artif Intell Rev 56(11):13373–13406

Fan P, Mishra AK, Feng S, Su M, Hirsch S (2023) The impact of China's new agricultural subsidy policy on grain crop acreage. Food Policy 118:102472. https://doi.org/10.1016/j.foodpol.2023.102472

Fragkos P, Paroussos L (2018) Employment creation in EU related to renewables expansion. Appl Energy 230:935–945. https://doi.org/10.1016/j.apenergy.2018.09.032

Gao P, Zhang K, Zheng P (2024) The impact of industrial digitization on the global value chains position: evidence from China's industry sectors[J]. Econ Anal Policy 82:147–162

Ge H, Li B, Tang D, Xu H, Boamah V (2022) Research on digital inclusive finance promoting the integration of rural three-industry. Int J Environ Res Public Health 19(6): 3363. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/ijerph19063363

Guchhait R, Sarkar M, Sarkar B, Yang L, AlArjani A, Mandal B (2024) Extended material requirement planning (MRP) within a hybrid energy-enabled smart production system. J Ind Inf Integr 42:100717. https://doi.org/10.1016/j.jii.2024.100717

Guo H (2024) The agricultural carbon reduction effect of digital rural construction under the dual carbon target. Public Lib Sci PLoS ONE 19(4):e0299233. https://doi.org/10.1371/journal.pone.0299233

Han J, Wang J, Zhang W (2023) Digital Adoption levels and income generation in rural households in China. Heliyon 9:e21045. https://doi.org/10.1016/j.heliyon.2023.e21045

Hu S, Jia N (2025) The impact of the 'full liberalization of household registration' policy on the free migration of rural labor. China Econom Rev 89:102330. https://doi.org/10.1016/j.chieco.2024.102330

Huang T, Quan Y, Li N (2024) Reallocate to the right place: the heterogeneous effect of internet use on factor allocation of rural households in China[J]. Econ Anal Policy 84:1328–1346

Huang X, Yang F, Fahad S (2022) The impact of digital technology use on farmers' low-carbon production behavior under the background of carbon emission peak and carbon neutrality goals. Front Environ Sci 10, Frontiers. https://doi.org/10.3389/fenvs.2022.1002181

Huang X, Fahad S, Yang F, Nie F (2024) Fiscal policy, green finance, and low carbon transformation nexus: a novel study unleashing the synergistic effects of carbon reduction and pollution in China. Environ Sci Pollut Res 31(3):4256–4268. https://doi.org/10.1007/s11356-023-31482-9

Irwin EG, Isserman AM, Kilkenny M, Partridge MD (2010) A century of research on rural development and regional issues[J]. Am J Agric Econ 92(2):522–553

Jänicke M (2012) 'Green growth': from a growing eco-industry to economic sustainability." Energy Policy, Special Section: Front Sustain 48:13–21. https://doi.org/10.1016/j.enpol.2012.04.045

Jermain DO, Pilcher RC, Ren ZJ, Berardi EJ (2024) Coal in the 21st century: Industry transformation and transition justice in the phaseout of coal-as-fuel and the phase-in of coal as multi-asset resource platforms. Energy Clim Change 5:100142. https://doi.org/10.1016/j.egycc.2024.100142

Ji X, Xu J, Zhang H (2023) Environmental effects of rural e-commerce: a case study of chemical fertilizer reduction in China. J Environ Manag 326:116713. https://doi.org/10.1016/j.jenvman.2022.116713

Jiang Q, Li J, Si H, Su Y (2022) The impact of the digital economy on agricultural green development: evidence from China. Agric Basel 12:1107. https://doi.org/10.3390/agriculture12081107

Jin M, Feng Y, Wang S, Chen N, Cao F (2024) Can the development of the rural digital economy reduce agricultural carbon emissions? A spatiotemporal empirical study based on China's provinces. Sci Total Environ 939:173437. https://doi.org/10.1016/j.scitotenv.2024.173437

Katoch OR, Sehgal S, Nawaz A, Cash TA (2024) Promoting sustainability: tackling energy poverty with solar power as a renewable energy solution in the Indian energy landscape. Discov Energy 4(1):24. https://doi.org/10.1007/s43937-024-00043-7

Khanna A, Kaur S (2023) An empirical analysis on adoption of precision agricultural techniques among farmers of Punjab for efficient land administration [J]. Land Use Policy 126:106533

Lajoie-O'Malley A, Bronson K, van der Burg S, Klerkx L (2020) The future(s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. Ecosyst Serv 45:101183. https://doi.org/10.1016/j.ecoser.2020.101183

Leng X (2022) Digital revolution and rural family income: evidence from China. J Rural Stud 94:336–343. https://doi.org/10.1016/j.jrurstud.2022.07.004

Li F, Zhang W (2023) Research on the effect of digital economy on agricultural labor force employment and its relationship using SEM and fsQCA methods[J]. Agriculture 13(3):566

Li F, Hou J, Yu H, Ren Q, Yang Y (2024) Harnessing the digital economy for sustainable agricultural carbon productivity: a path to green innovation in China. J Knowl Econ https://doi.org/10.1007/s13132-024-02158-7

Li G, Qin J (2022) Income effect of rural E-commerce: empirical evidence from Taobao villages in China. J Rural Stud 96:129–140. https://doi.org/10.1016/j.jrurstud.2022.10.019

Li X, Li Y, Chen Z (2024) Impact of rural e-commerce participation on farmers' household development resilience: evidence from 1229 Farmers in China [J]. Agriculture 14(5):692

Li X, Luo T (2010) Cointegration analysis of Hebei human capital's influence on rural labor non-agricultural employment. Statistic Application In Scientific And Social Reformation, K. L. Zhu and H. Zhang, eds., 212–215. Marrickville: Aussino Acad Publ House

Liu J, Wang X (2025) Exploring the driving effect of the digital economy on rural labor force's occupational transformation: based on analysis of CFPS panel data. Int Rev Financ Anal 101:104010. https://doi.org/10.1016/j.irfa.2025.104010

Liu Y, Chen W, Zhang X, Liao W (2025) Digital economy, consumption structure and rural economic transformation: a case study of China. Front Sustain Food Syst 9:1565067. https://doi.org/10.3389/fsufs.2025.1565067

Lu P, Li Z, Wu H (2024) Investigating the effects of industrial transformation and agglomeration on industrial eco-efficiency for green development: Evidence from enterprises in the Yangtze River Economic Belt. J Clean Prod 479:143949. https://doi.org/10.1016/j.jclepro.2024.143949

Lu H, Huan H (2022) Does the transfer of agricultural labor reduce China' s grain output? A substitution perspective of chemical fertilizer and agricultural machinery [J]. Front in Environ Sci 10:961648

Lu Y, Gao Y, Zhang Y, Wang J (2022) Can the green finance policy force the green transformation of high-polluting enterprises? A quasi-natural experiment based on "Green Credit Guidelines" [J]. Energy Econ 114:106265

Luo J, Huang M, Bai Y (2024) Promoting green development of agriculture based on low-carbon policies and green preferences: an evolutionary game analysis. Environ Dev Sustain 26(3):6443–6470. Dordrecht: Springer. https://doi.org/10.1007/s10668-023-02970-2

Mayer A (2022) Support for displaced coal workers is popular and bipartisan in the United States: evidence from Western Colorado. Energy Res Soc Sci 90:102593. https://doi.org/10.1016/j.erss.2022.102593

Pappas IO, Woodside AG (2021) Fuzzy-set Qualitative Comparative Analysis (fsQCA): guidelines for research practice in Information Systems and marketing. Int J Inf Manag 58:102310. https://doi.org/10.1016/j.ijinfomgt.2021.102310

Pei P, Zhang S, Zhou G (2024) Digital inclusive finance, spatial spillover effects and relative rural poverty alleviation: evidence from China. Appl Spat Anal Policy 17:1129–1160. https://doi.org/10.1007/s12061-024-09580-z

Pinheiro CPS, Silva LC, Matlaba VJ, Giannini TC (2022) Agribusiness and environmental conservation in tropical forestsin the eastern Amazon [J]. Sustainable Prod Consumption 33:863–874

Phan V-P (2023) Is the internet penetration pro-poor? Evidence from a panel data analysis [J]. Telecommun Policy 47(8):102612

Qiu H, Tang W, Huang Y, Deng H, Liao W, Ye F (2024) E-commerce operations and technology perceptions in promoting farmers' adoption of green production technologies: evidence from rural China. J Environ Manag 370:122628. https://doi.org/10.1016/j.jenvman.2024.122628

Qu Y, Fan S (2024) Is there a 'Machine Substitution'? How does the digital economy reshape the employment structure in emerging market countries. Econ Syst 48(4):101237. https://doi.org/10.1016/j.ecosys.2024.101237

Scur G, da Silva AVD, Mattos CA, Goncalves RF (2023) Analysis of IoT adoption for vegetable crop cultivation: Multiple case studies [J]. Technol Forecast Soc Change 191:122452
Shahzad MA, Razzaq A, Qing P, Rizwan M, Faisal M (2022) Food availability and shopping channels during the disasters: Has the COVID-19 pandemic changed peoples' online food purchasing behavior? Int J Disaster Risk Reduct 83:103443. https://doi.org/10.1016/j.ijdrr.2022.103443
Sun L, Zhu C (2022) Impact of digital inclusive finance on rural high-quality development: evidence from China. Discret Dyn Nat Soc 2022:7939103. https://doi.org/10.1155/2022/7939103
Tan L, Yang Z, Irfan M, Ding CJ, Hu M, Hu J (2024) Toward low-carbon sustainable development: exploring the impact of digital economy development and industrial restructuring [J]. Bus Strategy Environ 33(3):2159–2172
Tang W, Zhu J (2020) Informality and rural industry: rethinking the impacts of e-commerce on rural development in China [J]. J Rural Stud 75:20–29
Tiwasing P, Clark B, Gkartzios M (2022) How can rural businesses thrive in the digital economy? A UK perspective*. Heliyon 8:e10745. https://doi.org/10.1016/j.heliyon.2022.e10745
Ullo SL, Sinha GR (2021) Advances in IoT and smart sensors for remote sensing and agriculture applications [J]. Remote Sens 13(13):2585
Unay-Gailhard I, Bojnec S (2019) The impact of green economy measures on rural employment: Green jobs in farms. J Clean Prod 208:541–551. Oxford: Elsevier Sci Ltd. https://doi.org/10.1016/j.jclepro.2018.10.160
Wang L, Shao J (2023) Digital economy, entrepreneurship and energy efficiency [J]. Energy 269:126801
Wang Q, Xia X, Lan S, Li M (2023) Rural digital infrastructure and labor market: Evidence from universal telecommunication service. Asian Econ J 37:293–325. https://doi.org/10.1111/asej.12306
Wang X, Y Huang, Y Zhao, J Feng (2023) Digital Revolution and Employment Choice of Rural Labor Force: Evidence from the Perspective of Digital Skills. Agriculture, 13(6):1260. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/agriculture13061260
Wei Q, Jian C (2024) Impact of non-agricultural employment on industrial structural upgrading -Based on the household consumption perspective. PLoS ONE 19:e0294333. https://doi.org/10.1371/journal.pone.0294333
Xiong B, Sui Q (2025) The effect of digital economy on rural workforce occupation transformation ability: evidence from China. Hum Soc Sci Commun 12:13. https://doi.org/10.1057/s41599-024-04326-1
Xu N, D Zhao, W Zhang, M Liu, H Zhang (2022) Does digital transformation promote agricultural carbon productivity in China? Land, 11(11): 1966. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/land1111196
Yang G, Zhou C, Zhang J (2023) Does the synergy among agriculture, industry, and the service industry alleviate rural poverty? Evidence from China. Appl Econ Lett 30:1417–1421. https://doi.org/10.1080/13504851.2022.2056569
Yang J, R Yang, MH Chen, CH Su, Y Zhi, J Xi (2021) Effects of rural revitalization on rural tourism. J Hosp Tour Manag, 47:35–45. Amsterdam: Elsevier. https://doi.org/10.1016/j.jhtm.2021.02.008
Yuan Y, Guo X, Shen Y (2024) Digitalization drives the green transformation of agriculture-related enterprises: a case study of a-share agriculture-related listed companies. Agric Basel 14(8):1308. https://doi.org/10.3390/agriculture14081308
Zhan Y, Gao D, Feng M, Yan S (2025) Digital finance, non-agricultural employment, and the income-increasing effect on rural households. Int Rev Financ Anal 98:103897. https://doi.org/10.1016/j.irfa.2024.103897
Zhang G, N Zhang (2020) The effect of China's pilot carbon emissions trading schemes on poverty alleviation: A quasi-natural experiment approach. J Environ Manag 271: 110973. London: Academic Press Ltd- Elsevier Science Ltd. https://doi.org/10.1016/j.jenvman.2020.110973
Zhang H, Guo K, Liu Z, Ji Z, Yu J (2024) How has the rural digital economy influenced agricultural carbon emissions? Agricultural green technology change as a mediated variable. Front Environ Sci 12:1372500. https://doi.org/10.3389/fenvs.2024.1372500
Zhang J, Li M (2024) Digital technology access, labor market behavior, and income inequality in rural China. HELIYON 10:e33528. https://doi.org/10.1016/j.heliyon.2024.e33528
Zhang Y, Pi L, Chen Y, Shi R (2024) Energy transition policy and Chinese rural revitalization: The roles of industrial upgrading and digital economy. Financ Res Lett 69:106100. https://doi.org/10.1016/j.frl.2024.106100
Zhang Z, Sun C, Wang J (2023) How can the digital economy promote the integration of rural industries-taking China as an example. Agric Basel 13:2023. https://doi.org/10.3390/agriculture13102023
Zheng P, Li Y, Li X (2024) The impact of the digital economy on land transfer-out decisions among Chinese farmers: evidence from CHFS micro-data. Sci Rep. 14:19684. https://doi.org/10.1038/s41598-024-70605-1
Zhmud V, A Liapidevskiy, V Avrmachuk, V.Sayapin, O Stukach, H Roth (2021) Analysis of barriers to the development of Industrial Internet of Things technology and ways to overcome them. IOP Conf Ser Mater Sci Eng 1019(1):012079. IOP Publishing. https://doi.org/10.1088/1757-899X/1019/1/012079

## Acknowledgements

This research was funded by the Major Project of the Fujian Provincial Social Science Fund (FJ2025Z006).

## Author contributions

Hu Zhiguang is the sole author of this article, completing the data research, analysis, and writing of the paper.

## Competing interests

The authors declare no competing interests.

## Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

## Informed consent

This article does not contain any studies with human participants performed by any of the authors.

## Additional information

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