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Using Digital Intelligence to Boost Agriculture and Tourism Cooperation in Underdeveloped Regions of China

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Abstract: **This study explores how digital intelligence fosters the integration of agriculture and tourism industries in the less-developed areas of China, particularly in the former Central Soviet Area, spanning Jiangxi, Fujian, and Guangdong provinces. The analysis, based on data collected from 2012 to 2021, reveals that digital technologies like AI and 5G can significantly enhance the coordination between agriculture and tourism. The integration of these industries is examined through the impact of digital intelligence on industrial structures, consumer demand, and reducing barriers to entry for public services. Findings show that while digital intelligence has a positive effect across all regions, its impact is most profound in Jiangxi Province, where it has driven notable advances in agricultural modernization and rural tourism. The study emphasizes the role of government policies in supporting digital transformation and suggests strategies to maximize the benefits of digital intelligence for local development. The results offer valuable insights for other underdeveloped regions seeking to implement similar strategies.**

Keywords: **Digital Intelligence, Agricultural Integration, Tourism Development, Jiangxi, Rural Revitalization, Technological Empowerment, Industrial Synergy, Rural Economy, China.**

I. INTRODUCTION

Since the 1980s, China's economy has been marked by uneven regional development. The economic disparity between regions is widening, making coordinated regional development an urgent issue in China's growth. With increased support from the central government in recent years, the appearance of less-developed areas has seen significant changes. However, common problems such as poor natural conditions, slow economic growth, and low living standards still exist (S. Wang et al., 2021). At the industrial level, underdeveloped regions have long supported a large agricultural population and produced substantial agricultural output (Chen & Gong, 2021). Although agriculture has provided a strong foundation and resource advantages for these areas, issues like limited innovation, homogenization, and the slow pace of updating and improving regional agricultural products have not been effectively addressed (He et al., 2024).

To fully utilize agriculture's multiple functions and improve its productivity, the Chinese government has implemented a series of policies to promote the integration and development of agriculture with other industries. Among these, the integration of agriculture and tourism has grown rapidly in recent years (Wang, Xia et al., 2023). From 2011 to 2019, the number of registered private enterprises involved in leisure agriculture increased from over 26,000 to 216,000 (Zhou et al., 2021). Additionally, the operating income from leisure agriculture and rural tourism escalated from 216 billion yuan in 2011 to 850 billion yuan in 2019, according to the Ministry of Agriculture and Rural Affairs of China, representing 4.82% and 12.06% of the country's rural gross domestic product, respectively (China's rural GDP, estimated by the value added of the primary industry, was 4.48 and 7.05 trillion yuan in 2011 and 2019, according to the National Bureau of Statistics of

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China). However, due to factors such as economic development, geographical location, and ideology, most agro-tourism programs in these regions feature a single form of technological integration and lack innovation. Low-level activities, such as tea plantation visits, orchard visits, and selling agricultural products, are common (He et al., 2024). As a result, these areas have not been able to fundamentally shift away from traditional industrial development modes (Wen & Jiang, 2024).

To promote the high-quality development of agriculture and rural areas, it is essential to proactively follow the trend of digital and real integration and elevate agricultural and rural productivity to a new level. In this process, the role of digital intelligence is becoming increasingly important. As a result of digital technology advancing to higher levels of artificial intelligence, the cognitive, perceptual, and problem-solving capabilities generated by digital intelligence—created through intelligent algorithms and digital technologies—can be applied across a wide array of production and service scenarios (Rammer et al., 2022). It serves as a vital lever for transforming traditional industries and fostering new growth drivers (Zang et al., 2024). The emerging digital intelligence technology, led by 5G, promotes resource integration among agriculture, tourism, and other sectors, reconstructing industry chains, innovation chains, and value chains, thereby becoming the core technological support and crucial means for integrating agriculture and tourism (Charatsari et al., 2022). First, digital intelligence equips the system with independent data analysis, intelligent decision-making, and self-learning abilities, which facilitate optimal resource allocation between industries and support industrial upgrading (Zeng et al., 2021). This extends the inherent functions of agriculture and tourism, ultimately enabling their integration. Second, digital intelligence makes interconnected data more accessible for analysis and processing with practical tools, reducing barriers to public services (Zhong et al., 2022). It helps unlock the intrinsic resources of agritourism. Finally, digital intelligence employs representative technologies to establish ubiquitous connections across all fields, thereby stimulating consumers' dynamic demands (Heo & Lee, 2019). This encourages the expansion of the intrinsic market for agri-tourism.

Less-developed areas may benefit from latecomer advantages, where they can leverage advanced technology to accelerate industrial integration. Therefore, digital intelligence can be a breakthrough in local industrial modernization and a driving force for rural residents in these areas to cross the digital divide and achieve shared prosperity. Integrating agriculture and tourism industries can revitalize the rural economy, promote adjustments in the rural industrial structure, and realize rural revitalization.

However, digital intelligence must be tailored to local conditions to support the integration of agriculture and tourism industries. Taking China's old revolutionary base areas as an example, it's clear that most of these regions are border areas and mountainous zones, facing the dual challenges of economic growth and ecological conservation (Wen & Jiang, 2024). Among them, the former Central Soviet Area of Jiangxi, Fujian, and Guangdong Provinces is China's largest and most populous of the 13 old revolutionary base areas. These areas have made significant contributions and sacrifice for China's revolution. Because of the geographic proximity of Jiangxi, Fujian, and Guangdong Provinces, the entire region is strongly influenced by Hakka Culture and maintains a high level of traditional social interaction, making it more like a relatively self-sufficient economic system. The cities in this region have always been distant from the political and economic centers of Jiangxi, Fujian, and Guangdong Provinces, rendering it a politically marginalized and impoverished area within these three provinces (Zhang & Kong, 2022).

Additionally, the region has taken on nationally or regionally important ecological roles, and the level of national policies mainly relies on limited development (Y. M. Huang et al., 2024). As a result, the growth of agri-tourism needs to align with the national average for similarly underdeveloped regions. Therefore, this study selects the former Central Soviet Area of Jiangxi, Fujian, and Guangdong Provinces as a sample and uses it as a case to examine how less developed areas can achieve the integration of agriculture and tourism through digital intelligence, and to propose effective policy recommendations for exploration.

Using panel data from the old revolutionary base areas of Jiangxi, Fujian, and Guangdong Provinces from 2012 to 2021, this study examines the impact of digital and intelligent technologies on the integration of agriculture and tourism industries. The results show that digital intelligence can significantly promote the integration of these industries, with the industrial structure effect, threshold-lowering effect, and consumer demand effect playing positive moderating roles.

The potential contributions of this study are as follows: First, regarding the research topic, it adds to the understanding of how data and reality can be integrated. Previous research mainly focuses on how digital intelligence enhances enterprise management (Ferreira et al., 2019), with few studies exploring this in tourism. Some research on digital-real integration in less-developed areas also emphasizes digitization and rural development (J. Huang, 2018). Therefore, this study examines its effect on combining agriculture and tourism industries. It explains the empowering effects using the ‘‘ThreeChain’’ model, offering a comprehensive view of the underlying mechanism. Second, this study introduces a relatively new perspective. It is based on detailed data from prefecture-level cities in Jiangxi, Fujian, and Guangdong Provinces' old revolutionary base areas for the first time. It confirms that digital intelligence has a significant positive empowering effect on linking agriculture and tourism industries. In line with China's strategy to support the revitalization of old revolutionary base areas—such as a well-known historic revolutionary region—the findings provide decision-making support for developing locally tailored industrial strategies in these underdeveloped areas. Simultaneously, it offers a potential reference for other less developed regions seeking to realize their latecomer advantages in industrial growth.

The rest of this study is organized as follows: Chapter 2 introduces the mechanism of digital intelligence that enables the integration of agricultural and tourism industries. Chapter 3 describes the data and models. Chapter 4 presents the results and further discusses the impacts of digital intelligence, digitization, and intelligence on the integration of agricultural and tourism industries across different regions. Chapter 5 summarizes the research conclusions and offers the relevant policy implications.

II. LITERATURE AND THEORETICAL ANALYSIS

Existing research remains relatively limited in relevant fields, focusing more on the two aspects of digital intelligence to empower the agricultural and tourism industries. First, digitization enables these industries. Digitization includes various phenomena and technologies, such as big data, IoT, cloud computing, digital twins, and blockchain. These can be classified as physical technologies and non-physical technologies. From a physical technology standpoint, new devices like drones and robots improve precision agriculture and enhance production. From a non-physical technology perspective, digital technology is reflected through remote operations, such as remote agricultural extension, consulting services, and digital equipment management (Wolfert et al., 2017). It also facilitates the distribution and marketing of travel products through automation, such as e-tickets and online hotel reservations (Law et al., 2014). Second, intelligence advances the agricultural and tourism industries. Initially, smart farming (Wolfert et al., 2017) and precision farming (Wolf & Buttel, 1996) represented different forms of agricultural digitization, while concepts like smart tourism and cloud tourism appeared in the tourism sector. However, artificial intelligence is evolving from weak AI to strong AI. Intelligent devices and cloud computing increasingly support agricultural production and tourism services. Lioutas et al. (2019) note these technologies can offer smart insights for farmers, while Baggio and Cooper (2010) suggest they influence service processes, costs, and management methods for tourism businesses. According to Ivanov and Webster (2017), intelligent customer service, targeted information delivery, and robotic sensing notably impact tourists' needs, preferences, decisions, and experiences. However, despite its transformative potential, concerns exist regarding the digital farming movement. These include the digital divide between urban and rural areas, large and small farms, male and female farmers, as well as farmers in industrialized and developing countries (Aker et al., 2016). Data governance issues have also been raised (Bronson & Knezevic, 2016; Rotz et al., 2019). Therefore, the rise of digital intelligence technologies, exemplified by 5G, is expected to connect the agricultural and tourism industries, blur their boundaries, and foster their integration.

In 1958, American economist Hirschman first introduced the concept of the industrial chain from the perspective of forward and backward linkages in economic development strategy. Later, some scholars introduced related concepts, such as the value chain (Porter, 1985) and the innovation chain (Rothwell, 1992). Therefore, based on the studies of Y. Y. Wang (2022) and Dai (2022) and considering the perspectives of the industrial chain, innovation chain, and value chain, this study examines the enabling role of digital intelligence in integrating agricultural and tourism modernization.

First, consider the industry chain perspective: technology empowerment. The Industrial Integration Theory outlines the dynamic process where different industries or sectors within the same industry interact, overlap, and eventually merge, forming new industries over time (Li & Wang, 2002). Industrial integration promotes the innovation and upgrading of traditional industries and enhances the competitiveness of business entities. From this perspective, the core of digital and intelligent empowerment in agri-tourism integration is the joint advancement of digital and smart technology with the agritourism industry, digital economy, intelligent economic subjects, and agri-tourism operators. Digital intelligence offers new technological support for the agri-tourism sector. It speeds up the transformation of traditional agri-tourism projects into digital and intelligent formats by expanding, supplementing, and strengthening the industry chain. Conversely, the agritourism industry provides a foundation for developing digital intelligence. Big data technology helps consumers better understand current hotspots and trends in tourism development; blockchain technology offers end-to-end applications for

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tourists and improves transparency in the tourism process. 5G technology empowers related ecosystems and enables human-computer interaction scenarios in tourism through video. The introduction of AR and VR wearable devices creates immersive experiences for tourists. Mobile technology and cloud computing assist small farmers and major scenic spots in managing their businesses more efficiently, ultimately fostering integration between agriculture and tourism industries. Coordinating and sharing the entire process and application scenarios contribute to building a robust industrial chain.

Second, the perspective of the innovation chain: data empowerment. Schumpeter's Innovation Theory highlights combining traditional production factors in new ways and applying them to production systems, thus driving the emergence of new functions and productivity in five areas: new products, new technologies, new markets, new energy sources, and new combinations (Schumpeter, 1990). From this perspective, digital intelligence involves using digital and intelligent technology—two new factors of production—to empower various fields along the industrial chain, enabling digital and intelligent development of the chain's nodes. This shows that technological innovation plays a key role in industry development. Furthermore, from a technological revolution viewpoint, throughout human history, each wave of major technological change has profoundly shifted industrial paradigms. The rapid growth of the digital and intelligent economy has sparked a new phase of the Digital Intelligence Revolution. Compared to previous revolutions, the new industrial paradigm driven by this revolution breaks traditional boundaries and ignites extensive industrial integration. It leads to disruptive changes in product functions, production technologies, business models, and more (Kohli & Melville, 2019). At the intersection of agriculture and tourism, digital intelligence has transformed traditional industries' development methods and technical tools, supporting the building of digital villages and the integrated development of three industries. Therefore, technological innovation is essential for the deep integration of digital intelligence with agricultural tourism, and using this theory helps clarify its role as a factor of production and offers a solid basis for analyzing its impact on the industrial economy.

Data, as a new factor of production, can transcend regional boundaries, quickly reshape resource flows in existing sectors, enhance the integration with traditional resources, and increase output in traditional industries. The movement of data fosters the transfer of technology, capital, talent, and materials, leading to clustering and integration. This ultimately creates a dual cycle of factor flow both within and beyond the original area—helping to establish a new development balance. In agriculture, digital intelligence has driven transformation by improving operational efficiency through intelligent machinery and information platforms. For tourism, data has further blurred the lines between virtual and real worlds through emerging technologies like VR and AR, enriching the technological aspect of tourism experiences and offering diverse options. Particularly with the rise of the metaverse era, creating virtual cloud tourism routes can enhance immersive experiences, connect reality with virtuality, and develop new service and ecological models for agriculture and tourism industries, expanding the innovation chain.

Third, the perspective of the value chain emphasizes demand empowerment. According to the Collective Action Theory, common interests are promoted by negotiating shared action problems and providing public goods through relevant institutional arrangements such as channel maintenance (Mancur, 2017; Ostrom, 1990). It has been demonstrated that rural governance and development are intertwined with the collective actions of local governments, enterprises, rural collective economic organizations, and farm households (Y. H. Wang et al., 2022). Specifically, in the context of agricultural and tourism industry integration, the use of digital intelligence technology has created an effective collective decision-making and coordination platform for enterprises, consumers, locals, and other stakeholders. By integrating resources, this platform enables a dynamic match between needs of consumers and suppliers. For example, digital intelligence enhances the alignment of supply and demand between tourism businesses and tourists. On one hand, by adapting to local conditions, regional brand features and strengths are amplified to foster differentiated competition. On the other hand, online platform tools provide tourists with highly personalized experiences, increasing the visibility of tourist attractions and surrounding areas, and ultimately facilitating value co-creation among all stakeholders, thereby building the value chain. Based on this analysis, this study proposes the following hypothesis:

Hypothesis 1. Digital intelligence positively influences the integration of agricultural and tourism industries.

Schumpeter (1990) first introduced the theory of Integrated Innovation in the Theory of Economic Development. He explained that innovation involves recombining production factors within the production system to generate potential profits. The core of fusion innovation is a multiagent collaborative model that emphasizes resource integration, knowledge sharing, and value co-creation (Najafi-Tavani et al., 2018). Factors driving the integration of agricultural and tourism industries include technological, service, and product innovations, but fundamentally, these behaviors are sparked by element innovation. Additionally, integration mainly stems from two aspects: agricultural transformation and development, and the upgrading of tourism consumption supply and demand, both of which depend on interactions between industrial factors. Therefore, this study, grounded in the theory of fusion innovation and supply and demand, examines how digital intelligence influences the transmission mechanisms affecting the integration of the agricultural and tourism sectors, focusing on functions, resources, and markets.

First, consider the effect of industrial structure. Digital intelligence, enabled by artificial intelligence technology, allows systems to analyze data independently, make intelligent decisions, and learn to improve themselves. This promotes optimal resource allocation among industries and helps upgrade industrial structures. This effect enhances the intrinsic functions of agricultural and tourism industries, gradually integrating them. Similar to how digital industrialization and industrial digitization are classified in the digital economy, digital intelligence falls into two categories: digital intelligence industrialization and industrial digital intelligence. The former indicates the transformation of the primary industry to the tertiary industry, while the latter encourages the upgrading of agricultural and tourism sectors. Marx believed that new productive forces drive economic development. These forces optimize the industrial structure by creating new demand and supply, acting as the engine of economic growth (Heo & Lee, 2019). Digital intelligence reduces technical barriers in agriculture, tourism, and related services, reshaping business boundaries, lowering transaction costs, and expanding business opportunities. This fosters a more advanced industrial structure and fully activates the post productivism function of agricultural space (Wilson, 2001). Currently, cloud tourism, which uses digital media as a platform, has become a new leisure option. Tourists can explore destinations without leaving their homes (Scott et al., 2019). Digital landscapes, such as smart greenhouses, have become popular tourist attractions. Farmers can transform agricultural spaces into tourism venues through digital projects like picking experiences and sightseeing tours. The demand-driven development of digital intelligence reduces technological innovation risks for agricultural and tourism businesses. It also enhances the efficiency of innovation efforts, cuts costs, and supports industrial rationalization. Rationalization involves maximizing tourism service effectiveness, especially through rural live broadcasting showcasing fields and natural scenery. Hosts use local agricultural and tourism spaces to create popular products via online platforms, increasing scale and adding value to agricultural goods, ultimately integrating the functions of agriculture and tourism industries. Therefore, this study proposes the following hypothesis:

Hypothesis 2. Digital intelligence facilitates the integration of agricultural and tourism industries through the impact on the industrial structure.

Second, the threshold-lowering effect. Digital intelligence, enabled by technologies such as big data, cloud computing, and blockchain, provides practical tools and means for analyzing and processing interconnected data (Mithas & McFarlan, 2017), thus lowering the barriers to accessing public services. This effect encourages the expansion of internal resources in the agricultural and tourism industries and ultimately leads to their integration. Digital intelligence enhances the quality of tourism services and the efficiency of agricultural production by optimizing internal resource allocation in these industries. This reduces the barriers to internal resource sharing and boosts overall industry resource efficiency. Characteristics of digital intelligence technology, such as driving force, permeability, and multiplicity, foster the integration of agricultural and tourism development and facilitate the inter-regional flow of development elements. This lowers the barriers to industry interaction. An example of this is digital financial inclusion. Digital inclusive finance combines digital technology and financial services to offer diverse services and enhance the function of Internet-plus finance. On the supply side, digital inclusive finance can lower the security risks for rural residents. Additionally, it can decrease transaction costs and improve the business environment for farmers' entrepreneurship. On the demand side, digital inclusive finance can meet farmers' financing needs by providing a variety of extensive financial services, resulting in better benefits for farmers and integrating resource levels across agricultural and tourism industries. Therefore, this study proposes the following hypothesis:

Hypothesis 3. Digital intelligence facilitates the integration of agricultural and tourism industries through a threshold-lowering effect, thereby promoting their integration.

Third, consumer demand effect. Digital intelligence uses key technologies such as the mobile Internet, the IoT, and 5G to enable widespread connectivity among people, things, objects, and fields, thereby boosting social consumption demand. This consumer demand then helps expand the internal markets of agricultural and tourism industries and ultimately merges

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the two. The main contradiction in China has shifted to being between people's desire for a better life and unbalanced, inadequate development. The digital age marks a major change in people's consumption from material-oriented to spiritual-oriented. Farmers can learn digital technology and operational skills via the internet to become new farmers. This enables them to use digital tools in planting, production, processing, and other areas aligned with consumer demand, creating a vibrant market. Consumer demand is crucial in the market. It promotes the integration of agriculture and digital technology, optimizing land and resource use. On one side, it enhances the combination of agricultural reproduction and digital tools, improving land and resource efficiency. On the other side, it boosts farmers' income through land dividends and other assets, supporting the development of factor markets and enriching the agricultural and tourism sectors. This fosters a dynamic match between supply and demand in factor and product markets, resulting in a win-win situation. Therefore, the following hypothesis is proposed.

Hypothesis 4: The effect of consumer demand on digital intelligence.

Based on the analysis above, this study aims to incorporate digital intelligence, the integration of agricultural and tourism industries, the effects of industrial structure, the threshold-lowering effect, and the consumer demand effect into a unified analytical framework (Figure 1). This approach seeks to offer a new perspective for the main sectors of agricultural and tourism industries to achieve modernization and high-quality development through the use of digital intelligence tools.

III. RESEARCH DESIGN

This study selects 17 prefecture-level cities in the former Central Soviet Area of Jiangxi, Fujian and Guangdong Provinces from 2012 to 2021 as research samples, with 170 observations. As the largest and most populous revolutionary base established by the Communist Party of China (CPC) during the Agrarian Revolutionary War, this region belongs to typical underdeveloped areas (Wen et al., 2023) and has a strong sample representation. The data were mainly taken from the China Urban Statistical Yearbook, China Torch Statistical Yearbook, and provincial and municipal statistical yearbooks in previous years. This study shrinks the data at the [1%, 99%] level to eliminate the effect of extreme values. In addition, individual missing data are filled in using the domain mean method to mean-populate the missing data in the intermediate years. The linear interpolation method in the three-bar function interpolation, based on the assumption of a linear relationship, populates the missing values according to each individual's yearly trend. In order to reduce the indicator magnitude gap and the estimation bias caused by the model heteroskedasticity problem, the variables of the integration of agricultural and tourism industries and digital intelligence are standardized in the empirical regression. The collected digital intelligence-related indicators and the variables of the threshold-lowering effect, the consumption demand effect, education development, and economic growth are logarithmically processed.

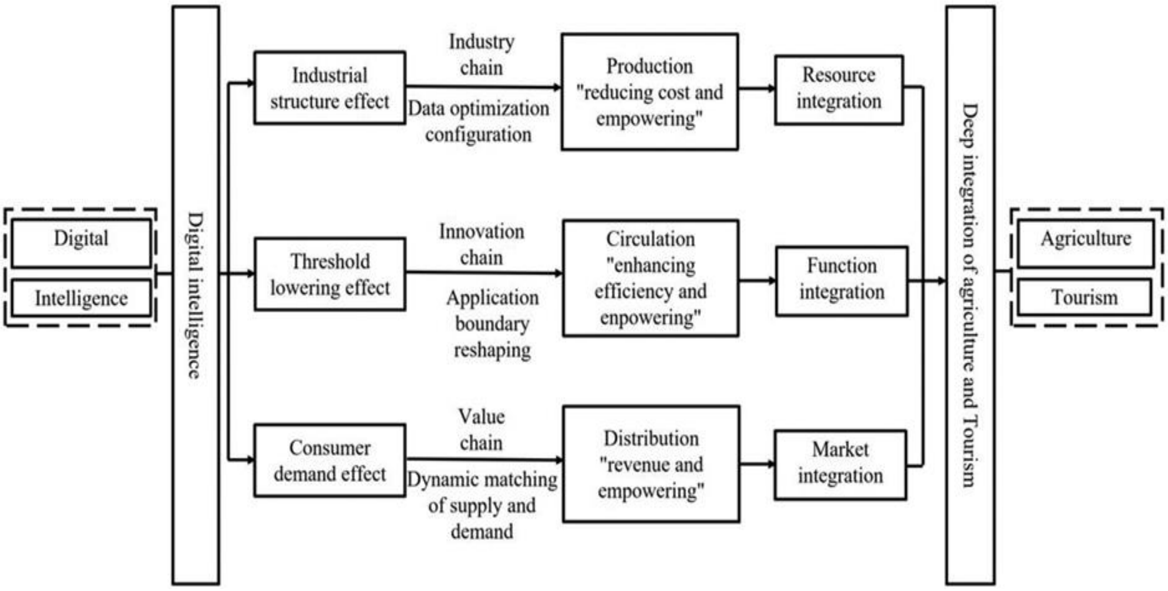

FIGURE 1: Theoretical analysis framework.

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In order to verify the positive empowering effect of digital intelligence on the integration of agricultural and tourism industries, this study constructs the following benchmark regression model:

$$Agr\_Tou_{i,t} = \alpha_0 + \alpha_1 Dig\_Int_{i,t} + \alpha_2 Controls_{i,t} + mi + vt + \epsilon_{i,t} \text{ ....(1)}$$

Where Agr_Tou denotes the level of integration of agricultural and tourism industries in city i in year t, $Dig\_Int_{i,t}$ denotes the level of digital intelligence in city i in year t, $Controls_{i,t}$ is the set of control variables, μ_i denotes the individual fixed effects of city i, v_t denotes the time fixed effects of year t, $\epsilon_{i,t}$ is the random disturbance term, and α_1 denotes the coefficients to be estimated. If α_1 is significantly positive, then Hypothesis1 and Hypothesis 2 are tested.

Further, to verify whether Hypothesis 2 to 4 is established and in order to reveal the intrinsic action mechanism of the integration of agricultural and tourism industries empowered by digital intelligence, this study designs the following mechanism testing model:

$$Inmedia_{i,t} = \beta_0 + \beta_1 Dig\_Int_{i,t} + \beta_2 Controls_{i,t} + mi + vt + \epsilon_{i,t} \text{ ....(2)}$$

$$Agr\_Tou_{i,t} = \gamma_0 + \gamma_1 Dig\_Int_{i,t} + \gamma_2 Controls_{i,t} + \mu_i + v_t + \epsilon_{i,t} \text{ ....(3)}$$

Where Inmediai,t is the set of mechanism variables, and the other variables have the same meaning as (1).

The dependent variable is the integration of agricultural and tourism industries (Agr_Tou). As a dynamic development process, the integration of agricultural and tourism industries is characterized by the selection of measurement indicators that reflect the respective development levels of agricultural and tourism industries and the interconnection between the two systems. Moreover, the above methods are prone to sample selection bias caused by the individual heterogeneity of survey respondents, and the endogeneity problem caused by unobservable variables is also inevitable to avoid. Therefore, this study refers to the method of Jiang et al. (2022) and adopts the coupling coordination degree model to evaluate the integration level of agricultural and tourism industries.

In terms of index selection, the agriculture indicators are constructed based on Lai et al.’s (2020) ideas and measured by agricultural factor input, agricultural output capacity and agricultural production sustainability. The tourism indicators are measured by the state of demand, resource base, and support condition. The details are shown in Table 1.

TABLE 1. Index System of the Integration of Agricultural and Tourism Industries.

First-Level Index	Second-Level Index	Indicator	Unit	Nature of indicators
Level of agricultural development	Agricultural factor inputs	Total power of agricultural machinery Number of electricity consumed in agriculture	10,000 kW 10,000 kWh	Positive Positive
	Agricultural output capacity	Gross agricultural output	10 million dollars	Positive
		Total grain production	ton	Positive
	Sustainability of agricultural production	Agricultural fertilizer application Agricultural pesticide use	ton ton	Negative Negative
Level of tourism development	State of demand	Number of tourists Revenue from tourism (million dollars)	10,000 people 10,000 yuan	Positive Positive
	Resource base	Number of A-class scenic spots	Number	Positive
		Total retail sales of consumer goods	10,000 dollars	Positive
	Support condition	Highway mileage	km	Positive
		Number of urban public toilets of category III or above	Seat	Positive

In terms of the processing method, to begin with, the entropy value method is used to measure the respective development levels of the agricultural and tourism industries (specific steps are omitted). Then, the coupled coordination degree model was selected to measure the level of integration between the two systems and their respective development levels in various regions. The calculation formula is as follows:

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$$D = \sqrt{2 - \frac{2\times(U_1^2+U_2^2)}{(U_1+U_2)}} \times \sqrt{\alpha U_1 + \beta U_2} \quad \ldots\ldots\ldots\ldots(4)$$

Where: U1 and U2 represent the comprehensive evaluation index of agricultural and tourism respectively, and D is the degree of coupling coordination; $\alpha U_1 + \beta U_2$ is the comprehensive coordination index of the two sub-systems, where a and b are the coefficients to be determined to reflect the contribution of the two systems. Agricultural and tourism industries intersect and integrate in a dynamic process of integration and development, and the study believes that for these areas, both are equally important in the coupled coordination system, so $\alpha=\beta=0.5$ is taken here (L. F. Wang, 2018; Wang, Zhou et al., 2023).

The core explanatory variable is digital intelligence (Dig_Int). There are few empirical studies on the development of digital intelligence in domestic and international academic circles and even fewer measurements for the new concept of digital intelligence. Instead, there are more studies on the development of the digital economy and digitization. Therefore, this study draws on the research constructed by Luo and Chen (2022) to create two first-level indicators of digitization and intelligence, which are then used to measure the indicators of digital intelligence. The index system has the advantages of spatial and temporal comparability and data stability for an accurate portrayal of digital intelligence in the Soviet areas of Jiangxi, Fujian, and Guangdong Provinces.

The first is the digital index (Dig). This study refers to the Report on China's Regional Digitization Development Index. It mainly draws on the research of Yu and Xiao (2023), who measure digitization using six indicators across three categories: digital infrastructure, digital application degree, and digital technology support.

The second is the intelligence index (Int). At present, research results on measuring the level of intelligence are limited and have not yet formed a unified system. This study adopts the approach proposed by Hou and Liu (2022) to construct indicators for measuring intelligence levels. These indicators are based on three aspects of intelligence: intelligent foundation, intelligent benefit, and intelligent innovation with six indicators. Specific indicators are shown in Table 2.

The weights of the fundamental indicators in the index system of digitization and intelligence are determined using Global Principal Component Analysis (GPCA). This method overcomes the limitation of classical principal component analysis that is only suitable for cross-sectional data and embeds the analysis of temporal dynamics in operation. The results reflect the trajectory of the overall level of the research sample over time (Vidal et al., 2005). In terms of the processing method, firstly, Principal Component Analysis (PCA) is applied to both the digital level and intelligence level. Then, GPCA is applied to both indicators to obtain the comprehensive digital intelligence level.

Table 2. Index System of the Level of Digital and Intelligence

Objective	First-Level Index	Second-Level Index	Indicator	Unit	Nature of Indicators
Level of Digital Intelligence	Digitization Index	Digital infrastructure	Internet broadband access rate	Percent	Positive
			Cell phone penetration rate	Percent	Positive
		Digital application degree	Total telecommunication services per capita	10,000 dollars/person	Positive
			Total postal operations per capita	10,000 dollars/person	Positive
		Digital technology support	Percentage of employees in the information transmission, computer services, and software industry	Percent	Positive
			Percentage of employees in the scientific research and technology services sector	Percent	Positive
	Intelligence Index	Intelligent foundation	Fixed investment in information transportation, software, and information technology	10,000 dollars	Positive
			Number of high-tech enterprises	Number	Positive

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Objective	First-Level Index	Second-Level Index	Indicator	Unit	Nature of Indicators
		Intelligent benefits	Revenue from telecommunication services	10,000 dollars	Positive
			Revenues from the manufacturing of computers, communications, and other electronic equipment	10,000 dollars	Positive
		Intelligent innovation	Number of authorized patent applications for inventions	Article	Positive
			Full-time equivalent of Research and Development (R&D) personnel	Person-year	Positive

Mechanism variables are the following three variables. First, industrial structure effect (Ind). The industrial structure effect makes agricultural, and tourism industries bound, forming the trend of bringing agriculture with tourism, thus expanding the corresponding share of the agricultural and tourism industries. The advanced industrial structure can not only reflect the coordination and reconstruction degree of the agricultural and tourism chain but also reflect the benefits of traditional agriculture from relying on nature to relying on people after the integration with the tourism industry. Therefore, this study uses the advanced industrial structure to measure the effect of industrial structure. Second, the threshold lowering effect (Thr). The rapid development of digital intelligence technology can expand the service scope of inclusive finance and reduce the entry barriers of financial institutions. This can accelerate the diffusion of capital flow, information flow, and talent flow, providing the possibility of generating innovative technologies in the agricultural and tourism industries. The economic inclusive effect facilitates the sharing of innovation risks and benefits among agricultural and tourism business entities, thus promoting in-depth cooperation and win-win situations among agricultural and tourism industries. Therefore, this study uses the digital finance index to measure the threshold-lowering effect. Third, the consumer demand effect (Con). Under the background of the ‘‘Digital Intelligence Revolution,’’ products, technologies and even business models are all involved in the trend of innovation, and agricultural and tourism enterprises need pursue profit maximization by satisfying consumers’ refined demand with personalized and technological supply. The total retail sales of consumer goods in the product market reflect not only the quality of agricultural manufactured products but also the scale of production and services in the factor market. The scale of factors behind it will flow into the agricultural and tourism enterprise sector again to promote the allocation and optimization of resources between the agricultural and tourism. Therefore, this study uses total retail sales of consumer goods per capita to measure the consumer demand effect.

In summary, industrial structure advanced (Ind), digital financial inclusion index (Thr), and total retail sales of consumer goods (Con) are selected as proxy variables to examine the industrial structure effect, the threshold lowering effect, and the consumer demand effect, and the specific calculation methods are shown in Table 3.

Table 3. Variable Definitions.

Variable type	Variable symbol	Variable names	Calculation methods
Dependent variable	Agr_Tou	The integration of agricultural and tourism industries	The degree of coupling coordination is measured by applying the coupling coordination model to the level of agricultural and tourism development
Independent variable	Dig_Int	Digital intelligence	Appraisal values measured using digital intelligence models
	Dig	Digital	Digitization Index constructed by GPCA
	Int	Intelligence	Intelligence Index constructed by GPCA
Mechanism variables	Ind	Industrial structure effect	The ratio of tertiary sector output to primary sector output
	Thr	Threshold-lowering effect	the Peking University Digital Financial Inclusion Index of China constructed by Guo et al. (2020)

	Con	Consumer demand effect	Total retail sales of consumer goods/resident population
Control variables	Edu	Educational development	Number of students enrolled in higher education/ resident population 3 100
	Gov	Government support	Expenditure on agriculture, forestry and water/expenditure on local public finance budget 3 100%
	Eco	Economic growth	GDP/resident population
	Urb	Urbanization	Urban population/resident population 3 100%
	Fin	Financial development	Financial sector value added/GDP 3 100%

In order to control the influence of other factors on the integration of agricultural and tourism industries, this study refers to the selection of Ma et al. (2023) and chooses the following indicators as control variables (as shown in Table 3): educational development (Edu), governmental support (Gov), economic growth (Eco), urbanization (Urb) and financial development (Fin). The details are shown in Table 4.

TABLE 4. Descriptive Statistics.

Variables	Observations	Mean	Std. dev.	Maximum	Minimum	Median
Agr_Tou	170	0.635	0.205	0.980	0.201	0.653
Dig_Int	170	4.34e-19	0.988	2.689	22.382	0.044
Dig	170	21.15e-10	0.736	2.030	21.879	20.052
Int	170	21.10e-10	0.736	1.901	21.845	0.001
Ind	170	0.943	0.310	1.629	0.482	0.867
Thr	170	5.269	0.079	5.821	4.353	5.357
Con	170	9.694	0.493	11.06	8.731	9.676
Edu	170	1.083	0.688	3.632	0.359	0.889
Gov	170	0.119	0.042	0.193	0.001	0.124
Eco	170	10.733	0.485	11.692	9.833	10.738
Urb	170	0.554	0.081	0.712	0.407	0.548
Fin	170	4.200	0.780	6.110	2.462	4.099

Table 4 shows the descriptive statistics of the variables analyzed in this study. It can be seen that there is little difference between the mean and the median, indicating that the sample follows an approximately normal distribution. Regarding the level of digital intelligence, the maximum value is 2.53 and the minimum value is 22.171, which is less than 0, indicating that the level in this region has realized a quantum change to a qualitative change in the past 10years. In terms of the level of education development, there is a difference of 0.2 between the average and the median, and the influence of extreme values cannot be excluded. There may be a gap between talent reserves and education development in different regions. The maximum value of government support is close to 0.2, and the minimum value is almost 0, indicating that the government's support for the agricultural and tourism industries has significant regional heterogeneity. This also highlights the importance of the government's top-level design and funding policy tilt. The other indicators are consistent with reality.

IV. EMPIRICAL RESULTS AND DISCUSSION

This study examines the coupling and coordination degree of the integration of agricultural and tourism industries, referring to Ma et al. (2023) and Liao (1999). The coupling and coordination degree of the two industries is classified into three types (Table 5). Additionally, the study synthesizes the coupling coordination degree of each city and region from 2012 to 2021, along with its corresponding coordination type (Table 6). Due to space limitations, this study shows data for the four time sections of 2012, 2015, 2018, and 2021.

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TABLE 5. Classification System of Coordinated Development of the Agricultural and Tourism Industries and Its Discriminating Criteria.

The first dimension		
D		Level of coordination
Strong correlation (acceptable ranges)	(0.9001,1)	Quality coordination
	(0.8001,0.9)	Good coordination
	(0.7001,0.8)	Intermediate coordination
	(0.6001,0.7)	Primary coordination
Medium correlation (transition ranges)	(0.5001,0.6)	Barely coordinated
	(0.4001,0.5)	On the verge of becoming dysfunctional
Weak correlation (unacceptable ranges)	(0.3001,0.4)	Mild disorder
	(0.2001,0.3)	Moderate disorder
	(0.1001,0.2)	Severe disorder
	(0,0.1)	Extreme disorder
The second dimension The contrast between U1 and U2		Type of coordination
U1.U2		Agriculture-led
U1=U2		Synchronous agricultural and tourism industries
U1\U2		Tourism-led

TABLE 6. Coordination Degree and Type of Agricultural and Tourism Industries Coupling From 17 Cities in 2012, 2015, 2018, and 2021

Municipalities	2012	Property	2015	Property	2018	Property	2021	Property
Ganzhou	0.212	Moderately dysfunctional development category, agriculture-led	0.432	Endangered Dysfunctional Development Category, Agriculture-led	0.742	Intermediate coordinated development category, tourism-led	0.981	Quality and coordinated development category, tourism-led
Ji'an	0.178	Heavily dysfunctional development category, agriculture-led	0.469	Endangered Dysfunctional Development Category, Agriculture-led	0.676	Primary coordinated development category, agriculture-led	0.980	Quality coordinated development category, tourism-led
Xinyu	0.229	Moderately dysfunctional development category, agriculture-led	0.509	Barely dysfunctional development category, agriculture-led	0.782	Intermediate coordinated development category, tourism-led	0.940	Quality coordinated development category, tourism-led
Fuzhou	0.224	Moderately dysfunctional development category, agriculture-led	0.558	Barely dysfunctional development category, agriculture-led	0.786	Intermediate coordinated development category, tourism-led	0.931	Quality coordinated development category, tourism-led
Shangrao	0.175	Heavily dysfunctional development category, agriculture-led	0.545	Barely Dysfunctional Development Category, Tourism-led	0.754	Intermediate coordinated development category, tourism-led	0.986	Quality coordinated development category, tourism-led
Yichun	0.309	Mildly dysfunctional developmental category, agriculture-led	0.555	Barely Dysfunctional Development Category, Tourism-led	0.805	Well-coordinated development category, tourism-led	0.971	Quality coordinated development category, tourism-led

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Municipalities	2012	Property	2015	Property	2018	Property	2021	Property
Pingxiang	0.260	Moderately dysfunctional development category, agriculture-led	0.487	Endangered Dysfunctional Development Category, Tourism-led	0.711	Intermediate coordinated development category, tourism-led	0.875	Well-coordinated development category, tourism-led
Yingtan	0.267	Moderately dysfunctional development category, agriculture-led	0.463	Barely dysfunctional development category, agriculture-led	0.759	Intermediate coordinated development category, tourism-led	0.932	Quality coordinated development category, tourism-led
Jiangxi Region	0.232	Moderately dysfunctional development category, agriculture-led	0.502	Barely Dysfunctional Development Category, Tourism-led	0.751	Intermediate coordinated development category, tourism-led	0.950	Quality coordinated development category, tourism-led
Longyan	0.243	Moderately dysfunctional development category, agriculture-led	0.608	Primary coordinated development category, agriculture-led	0.733	Intermediate coordinated development category, tourism-led	0.889	Well-coordinated development category, tourism-led
Sanming	0.270	Moderately dysfunctional development category, agriculture-led	0.589	Barely dysfunctional development category, agriculture-led	0.713	Intermediate coordinated development category, tourism-led	0.842	Well-coordinated development category, tourism-led
Nanping	0.230	Moderately dysfunctional development category, agriculture-led	0.651	Primary coordinated development category, agriculture-led	0.831	Well-coordinated development category, tourism-led	0.911	Quality coordinated development category, tourism-led
Zhangzhou	0.292	Moderately dysfunctional development category, agriculture-led	0.555	Barely dysfunctional development category, agriculture-led	0.667	Primary coordinated development category, tourism-led	0.875	Well-coordinated development category, tourism-led
Quanzhou	0.319	Moderately dysfunctional development category, agriculture-led	0.585	Barely dysfunctional development category, agriculture-led	0.726	Intermediate coordinated development category, tourism-led	0.853	Well-coordinated development category, tourism-led
Meizhou	0.425	Endangered Dysfunctional Development Category, Tourism-led	0.673	Primary coordinated development category, tourism-led	0.781	Intermediate coordinated development category, tourism-led	0.842	Well-coordinated development category, agriculture-led
Heyuan	0.398	Mildly dysfunctional developmental category, agriculture-led	0.557	Barely dysfunctional development category, agriculture-led	0.700	Intermediate coordinated development category, tourism-led	0.899	Well-coordinated development category, agriculture-led
Chaozhou	0.407	Endangered Dysfunctional Development	0.586	Barely Dysfunctional Development	0.765	Intermediate coordinated development	0.818	Well-coordinated development category, agriculture-led

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Municipalities	2012	Property	2015	Property	2018	Property	2021	Property
		Category, Agriculture-led		Category, Tourism-led		category, tourism-led		
Shaoguan	0.509	Barely dysfunctional development category, agriculture-led	0.521	Barely Dysfunctional Development Category, Tourism-led	0.830	Well-coordinated development category, agriculture-led	0.840	Well-coordinated development category, tourism-led
Fujian Region	0.435	Endangered Dysfunctional Development Category, Tourism-led	0.584	Barely dysfunctional development category, agriculture-led	0.769	Intermediate coordinated development category, tourism-led	0.850	Well-coordinated development category, tourism-led

From 2012 to 2021, the coupling and coordination degree between the agricultural and tourism industries in the cities is generally reasonable. In addition, the region has made significant progress in terms of coordination levels, moving from moderate dysfunction to high quality coordination. By 2018, all cities had reached at least the primary coupling coordination level, which is considered an acceptable range for agritourism integration. This achievement marks a significant milestone in the development of agritourism. The reason for this is that China proposed the Rural Revitalization Strategy in 2017, which emphasized the need to deepen the structural reform of the agricultural supply side and solve the issues concerning agriculture, countryside, and farmers. Therefore, while agriculture is revitalized, tourism has a catalytic effect and an excellent driving effect.

Among the coupling types of agricultural and tourism integration in each region of its cities, Guangdong Province, as a coastal province, developed their tourism industry earlier. It is evident from the coordinated types of 2011; Guangdong Province began piloting the Construction of Beautiful Village. The government has provided strong support for rural farmers, and the integration of agritourism has led to development. As a result, the coupling coordination degree between the depth of the agricultural and tourism industries in the Guangdong Region in 2012 was relatively high, with all of them having mild disorder or above. By 2021, the Jiangxi Region has realized the later on, the coupling degree of coordination of municipalities to reach a good or even high-quality coordination level, far more than the other two regions of prefecture-level cities, but also realized the transformation from a large agricultural region to a strong regionof tourism (in 2021, Jiangxi Region prefecture-level cities are all tourism-led). It may be that during the ‘‘13th Five-Year Plan’’ period, Jiangxi Province vigorously promoted the development of ‘‘Regional Tourism.’’ The construction of modern agriculture is actively integrated into the elements of tourism, the depth of the integration of agricultural and tourism, and the interactive development has achieved remarkable results. Among them, the coupling coordination degree of Ganzhou City in 2021 is 0.981, the highest level of all prefecture-level cities. Ganzhou’s continuous efforts in constructing a modern industrial system have also been verified as a demonstration zone for the high quality development of underdeveloped regions. In order to visualize the development speed of the level of digital intelligence in each region, this study will use 2012, 2015, 2018, and 2021 to show the scores (as shown in Figures 2–4). Additionally, this study selects the data from four cross-sections(2012, 2015, 2018, and 2021) to show the changes in the ranking of each city’s digital intelligence level score (Table 7).

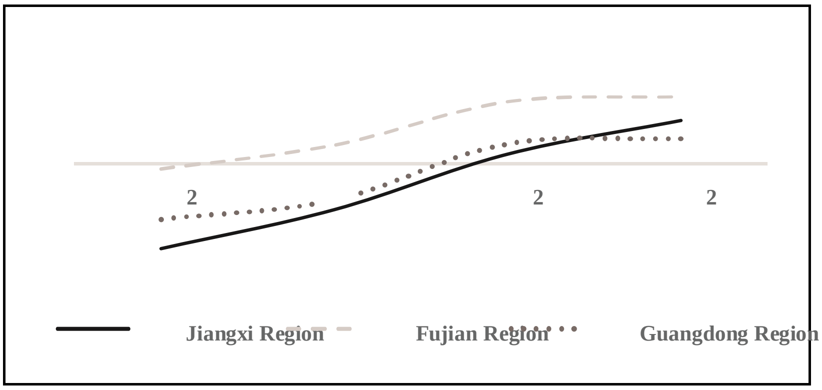

Figure 2. The development speed of digital intelligence of 3 regions in 2012 and 2021.

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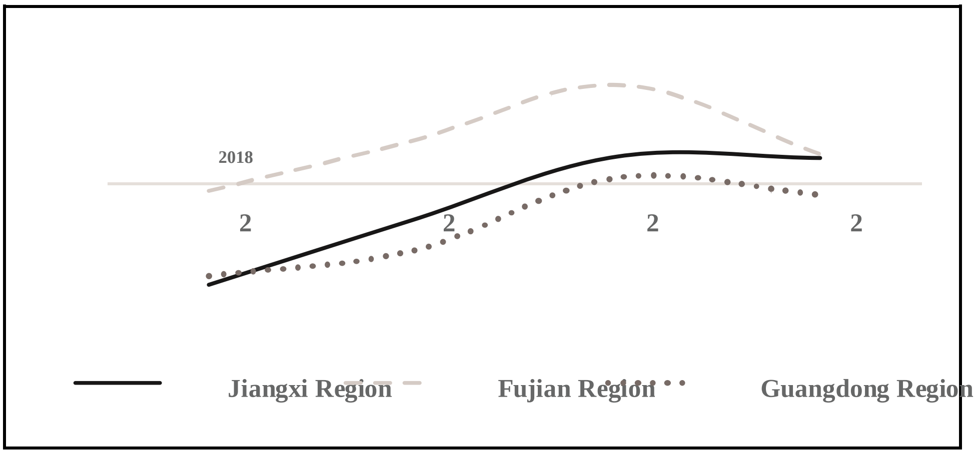

Figure 3. The development speed of digital of 3 regions in 2012 and 2021.

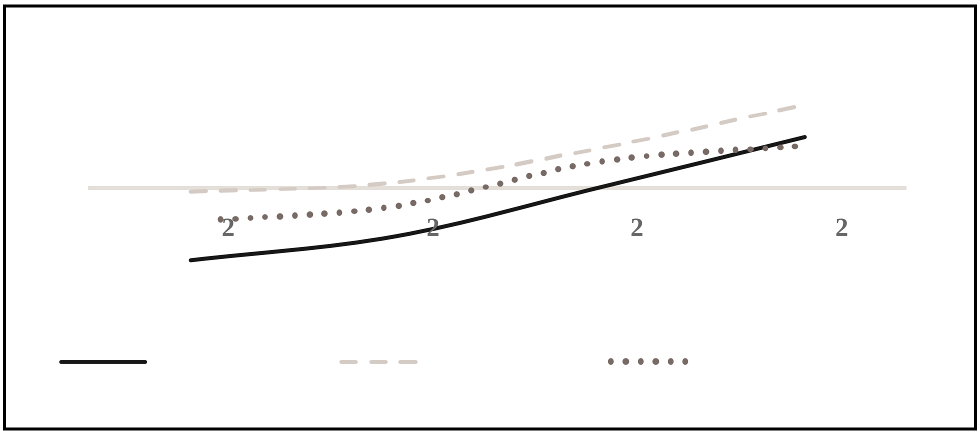

Figure 4. The development speed of intelligence of 3 regions in 2012 and 2021.

Table 7. Ranking of Digital Intelligence Level Scores of 17 Cities in 2012, 2015, 2018, and 2021.

City	2012	2015	2018	2021	City	2012	2015	2018	2021
Ganzhou	11	1	2	2	Sanming	9	7	8	9
Ji'an	13	5	9	13	Nanping	2	3	4	11
Xinyu	17	17	17	12	Zhangzhou	3	4	3	3
Fuzhou	16	12	14	6	Quanzhou	1	2	1	1
Shangrao	5	8	6	5	Meizhou	6	6	10	15
Yichun	8	10	7	4	Heyuan	12	14	13	14
Pingxiang	15	13	16	16	Chaozhou	7	15	12	8
Yingtan	14	16	15	17	Shaoguan	10	9	5	10
Longyan	4	11	11	7					

From a horizontal perspective, the chart illustrates that the prefecture-level cities in 3 Regions have better advanced digital and intelligence technology. However, between 2018 and 2021, the cities have not yet made significant breakthroughs. The reason may be that due to the external impact of the COVID-19 epidemic, enterprises lack the corresponding funds to install and maintain the digital system, which effectively affects the digital subsystem. From a vertical perspective, the Fujian Region has maintained steady growth in the development of digital and intelligence. At the turn of the century, Fujian Province grasped the trend of information technology development and planned and deployed the construction of ''Digital Fujian''. It can be seen that the Jiangxi Region is narrowing the digital intelligence gap with the other two regions. The reason may be that the other two coastal provinces are at the forefront of economic development and modernization and have already gone through a period of technological dividends. In details, in 2012, 2015, 2018, and 2021, Ganzhou City and Quanzhou City will be ranked 11, 1, 2, 2 and 1, 2, 1, 1, respectively. These cities are at the forefront of the digital and intelligence revolution.

In order to verify from Hypothesis 2 to Hypothesis 4, this study examines the industrial structure effect, threshold lowering effect and consumer demand effect as mediating variables. It investigates how digital intelligence empowers the integration of agricultural and tourism industries. Regression results are presented in Table 10. Columns (1) and (2) show the results of the industrial structure effect. It can be found that the fitting coefficients of digital intelligence on the industrial structure effect and the industrial structure effect on the integration of agricultural and tourism industries are both significantly positive at the 1% level. This suggests that digital intelligence can indeed enhance the integration of agricultural and tourism industries by promoting the upgrading of industrial structures. Columns (3) and (4) display the results of the threshold lowering effect. It can be found that the fitting coefficients of digital intelligence on the threshold-lowering effect and the threshold-lowering effect on the integration of the agricultural and tourism industries are both significantly positive at the 1% level. This indicates that digital intelligence can indeed lower the threshold of financial services and facilitate the integration of agricultural and tourism industries. Columns (5) and (6) present the results of the consumer demand effect. It can be found that the fitting coefficients of the effect of digital intelligence on consumption demand and the effect of consumption demand on the integration of agricultural and tourism industries are significantly positive at the 5% and 1% levels, respectively. This denotes that digital intelligence can indeed enhance consumption demand and contribute to the integration of agricultural and tourism industries.

V. CONCLUSIONS AND POLICY IMPLICATIONS

Digital intelligence empowerment has been a hot research topic in recent years. Based on the panel data of 17 prefecture-level cities in the former Central Soviet Area of Jiangxi, Fujian and Guangdong Provinces from 2012 to 2021, this study examined the impact of the integration of agricultural and tourism industries empowered by digital intelligence. After a series of empirical tests, the following conclusions are drawn:

- The level of digital intelligence in the prefectures of the region of Jiangxi, Fujian and Guangdong Provinces has generally shifted from negative to positive, of which Ganzhou and Quanzhou Cities have the highest comprehensive score of digital intelligence.
- The integration between the agricultural and tourism industries has realized a six-level leap from moderate disorder—barely coordinated—primary coordination—intermediate coordination—good coordination—quality coordination, of which all cities reached the primary and above coupling coordination level in 2018.
- There is a significant positive empowering effect of digital intelligence on the integration of agricultural and tourism industries. The findings of this study remain robust even after regressing with instrumental variables, changing the sample capacity, and replacing the core explanatory variable measurement method.
- The analysis of regional heterogeneity shows that digital intelligence can promote the integration of agricultural and tourism industries. However, the technological dividends empowered by digital intelligence in Jiangxi Region are greater than those in the two regions of Fujian and Guangdong Regions. Specifically, from the perspective of the digital intelligence subsystem, digitization has a significant positive impact on the integration of agricultural and tourism industries in the prefecture-level cities where the old revolutionary base areas in the three regions are located, among which the impact effect on Jiangxi Region is more apparent. However, intelligence contributes less to their integration than digitization.

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