Research On the Improvement Effect of Migrant Workers' Employment Quality Based on The Micro Perspective of Digital Rural Construction

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Abstract. Improving the employment quality of migrant workers is a crucial lever for promoting rural revitalization and urban-rural integration. Based on the matching data of Digital Rural County Index and China Family Panel Studies database in 2018 and 2020 , this paper examines the impact of digital village development on the employment quality of migrant workers, as well as the underlying mechanisms. The empirical results indicate that digital village development significantly enhances the employment quality of migrant workers. Mechanism analysis reveals that such development contributes to this improvement by facilitating the upgrading of the industrial structure and the transition toward a more skilled employment structure. Expansion analysis further suggests that the digitalization of the rural economy exerts the most pronounced effect on employment quality. This study argues that the role of digital village development in promoting high-quality employment for migrant workers should be further strengthened, thereby advancing comprehensive rural revitalization and empowering the realization of the strategic goal of common prosperity.

Keywords: Digital Rural, Employment Quality, Migrant Workers, Inclusiveness.

1. Introduction

In 2018, China first proposed the implementation of the “Digital Village Strategy” to bridge the urban-rural digital divide. Thus, digital village construction is a means, process, and state of restructuring rural economic development, driven by the digital economy, supported by modern information networks, and powered by advanced digital technologies [1].

Labor demand is a derived demand. The application of the digital economy in economic and social development has brought about structural adjustments in labor demand, serving as a crucial driver for upgrading the employment structure of migrant workers and improving their employment quality [2]. On one hand, rural China traditionally relies on customary norms to maintain social order, with limited information exchange and slow information renewal. The disembedding nature of digital village development, activates embedded resources and elements such as latent market opportunities, dormant capital, and local talents [3], deepens the division of labor, and upgrades both the structure and level of labor demand for migrant workers.On the other hand, in an imperfectly competitive market with information asymmetry, wages are influenced by the bargaining power of both labor and firms[4]. According to wage bargaining theory, abundant employment opportunities and higher levels of human capital enable migrant workers to escape the secondary labor market, enhance their bargaining power, and improve employment quality [5]. Digital village construction generates a range of digitally empowered effects. The informatization and intelligentization of rural areas accelerate industrial restructuring and drive continuous adjustments in labor demand. Labor demand information becomes concentrated on digital platforms, reducing search costs in traditional labor markets, facilitating dense markets and economies of scale [6], and offering broad employment opportunities for migrant workers in sectors such as e-commerce, logistics, and digital agriculture. Furthermore, digital village initiatives help address the underprovision of educational infrastructure in rural areas, alleviate the financial burden of educational investment for migrant workers, promote real-time sharing of educational resources, and expand learning and vocational training channels. Therefore, this paper argues that digital rural construction can significantly improve the employment quality of migrant workers.

Industrial upgrading refers to the shift, driven by continuous economic development, from labor-intensive, low value-added industries to high-tech, high value-added industries. This transition is typically reflected in the increasing proportion of output from the primary, secondary, and especially tertiary sectors [7]. In traditional labor markets, migrant workers are often engaged in highly repetitive, physically demanding, and hazardous jobs. Digital village development facilitates the deep integration of digital technologies into the tertiary sector, propelling it to become the main engine of economic growth. This transformation substitutes migrant workers out of highly repetitive and codifiable tasks and enhances their access to higher-quality employment opportunities, thereby improving employment quality. Digital village initiatives significantly differentiate the employment-generating capacities of various industries. Labor-intensive and low-to-medium-tech manufacturing sectors are experiencing a contraction in employment space, while emerging industries—such as producer and consumer services—exhibit strong labor demand, thereby driving a transformation in the structure of employment skills [8]. Simultaneously, in order to adapt to the demands of industrial upgrading, migrant workers may actively or passively engage in education and training, facilitating their mobility toward more efficient and skill-intensive jobs. Therefore, this paper argues that digital rural construction can significantly improve the employment quality of migrant workers by optimizing the industrial structure and improving the employment structure.

Although the existing literature directly discusses the relationship between the two, there are still the following shortcomings. First, existing studies primarily rely on cross-sectional data, which introduces randomness and limits the generalizability of findings. Second, the underlying mechanisms have not been adequately examined at the macro level, and issues such as data inconsistency and model endogeneity undermine the robustness of results, preventing a comprehensive and objective understanding of the influence pathways. In response, this study builds upon existing literature by adopting a holistic framework of digital village development. It employs matched data from the Index of Digital Rural County developed by the Institute of New Rural Development of Peking University and the China Family Panel Studies (CFPS) to empirically examine the impact of digital village construction on migrant workers' employment quality and its underlying mechanisms.

2. Research design

2.1. Data Sources

The data used in this study are drawn from three main sources: Micro-level individual data on migrant workers are derived from the CFPS 2018 and CFPS 2020 waves. Data on the level of digital village development are obtained from the County-Level Digital Village Index (2018 and 2020), jointly released by the Institute of New Rural Development at Peking University and the Ali Research Institute. Macro-level data are sourced from the China Statistical Yearbook and the China Labor Statistical Yearbook.The micro- and macro-level datasets are matched at the provincial level, and the sample is restricted to counties within the Yangtze River Economic Belt. In accordance with the official definition provided by the National Bureau of Statistics, individuals are classified as migrant workers if they (a) hold agricultural household registration or have converted to urban registration from agricultural status, and (b) are engaged in non-agricultural employment. Additionally, the sample is restricted to individuals aged 16 to 65. Observations with substantial missing values, those currently enrolled in school, or those who have exited the labor market are excluded. The final sample consists of 1292 observations of migrant workers.

2.2. Variable Definitions and Descriptive Statistics

2.2.1 Dependent Variable: Quality

A composite index of employment quality is constructed based on four dimensions: work income, job stability, social security, and work intensity [5,9]: (a) Work income: Measured by post-tax wage income from the respondent's primary job over the past 12 months. (b) Job stability: Equals 1 if a written labor contract is signed between the migrant worker and the employer; 0 otherwise. (c) Social security: Based on participation in five types of insurance—basic medical, pension, work injury, maternity, and unemployment—each assigned one point, summed to form the total score. (d) Work intensity: Measured by weekly working hours.The index is constructed as follows:

Step 1: Standardize each sub-indicator:

$$X_{ij}^{nor} = \frac{X_{ij} - min_j}{max_j - min_j} \tag{1}$$

In Equation(1), X_{ij}^{nor} denotes the standardized score for individual i on sub-indicator j, with max_j and min_j representing the maximum and minimum values of indicator j, respectively. Since work intensity is a negatively oriented indicator, it is transformed by subtracting the standardized value from 1 to reflect its inverse relationship with employment quality.

Step 2: Assign weights to sub-indicators. Following the approach of the European Commission and the European Foundation for the Improvement of Living and Working Conditions, equal weighting is applied to compute the employment quality index. For self-employed individuals, the employment quality index excludes job stability and is calculated based on the remaining three indicators.

$$Q_i = \frac{1}{4}\sum_{j=1}^{4} X_{ij}^{nor} \tag{2}$$

2.2.2 Core Independent Variable: Digital

The digital rural structure index encompasses four dimensions—rural infrastructure,rural economy, rural livelihood, and rural governance—and effectively captures the level of digital village development. Following the methodology of the referenced report, provincial-level digital village development is measured by the average of county-level indices within each province. Corresponding sub-indices are computed for each primary dimension (infrastructure, economy, governance, and livelihood) and standardized using Z-scores.

2.2.3 Mechanism Variable

The mechanism variables in this paper are the industry structure upgrade and the employment skill structure. To quantify industry structure upgrade, this study follows the method proposed by Fu (2010) [7]. Specifically, the industry structure upgrade index *Upgrade* is calculated as follows:

$$\theta_j = \left(\frac{\sum_{i=1}^{3}\left(x_{i,j} \cdot x_{i,0}\right)}{\sum_{i=1}^{3}\left(x_{i,j}^2\right)^{\frac{1}{2}} \cdot \sum_{i=1}^{3}\left(x_{i,0}^2\right)^{\frac{1}{2}}} \right) \quad (i, j = 1,2,3) \tag{3}$$

$$Upgrade_j = \sum_{k=1}^{3}\sum_{j=1}^{k} \theta_j \tag{4}$$

In Equation (3), the shares of value added from the primary, secondary, and tertiary industries in GDP are first calculated and denoted as components $x_{i,0}$ to form a three-dimensional vector $X_0 = (x_{1,0}, x_{2,0}, x_{3,0})$. The angles θ_1, θ_2, θ_3 between X_0 and the benchmark vectors representing industrial hierarchies—namely $X_1 = (1,0,0), X_2 = (0,1,0)$ and $X_3 = (0,0,1)$—are then calculated. Finally, the industrial upgrading index *Upgrade* is obtained according to Equation (4).

Regarding the employment skill structure, this paper follows the approach of Sun & Guo (2021) by using the proportion of workers with different educational attainments to measure employment across skill levels. Based on the Ministry of Education's classification, education is divided into six categories: postgraduate (including master's and doctoral degrees), undergraduate, junior college, high school, middle school, and primary school or below. Workers with junior college education and above are classified as high-skilled, those with high school or middle school education as medium-skilled, and those with primary school or below as low-skilled. The ratio of high-skilled to medium- and low-skilled workers *Skill* is used to capture the employment skill structure at the provincial level.

2.2.4 Control Variable

Multiple factors may influence the employment quality of migrant workers; however, excessive or inappropriate controls can lead to overfitting and multicollinearity, introducing estimation bias. To ensure scientific rigor in variable selection, this study employs the Lasso algorithm to select control variables at the individual, household, and provincial levels. Definitions and descriptive statistics of these variables are presented in Table 1.

Table.1. Descriptive Statistics

Variables	Definition	Mean	SD	Min	Max
Quality	comprehensive index	0.0967	0.0612	0.000185	0.233
Total Index of Digital Rural	Total Index	0.246	1.276	-1.617	2.266
Infrastructure	Sub-index	1.250	1.694	-2.179	3.921
Economy	Sub-index	-0.105	1.419	-2.158	1.980
Governance	Sub-index	-0.318	1.263	-2.150	2.279
Life	Sub-index	-0.0616	1.380	-2.380	1.981
Gender	Male=1, Female=0	0.574	0.495	0	1
Age	Age(years)	37.88	10.96	17	64
Marital Status	Married=1, Unmarried=0	0.794	0.405	0	1
Politics Status	Members of CPC=1, Others=0	0.00697	0.0832	0	1
Schooling	The logarithm of the actual years of education (in years)	2.266	0.616	0	2.833
Physical Condition	Very health=5, Quite health=4, Relatively healthy=3, Average =2, Unhealthy=1	3.204	1.017	1	5
Family Population Size	ln (total family population size)	1.262	0.564	0	2.708
Household Expenditure	ln (total household expenditure)	10.64	1.047	0	13.82
Economic Development	ln GDP	4.845	0.141	4.605	5.084
Human Capital	$\ln \frac{\text{education expenditure}}{GDP}$	0.0338	0.00977	0.0221	0.0642
Population	ln (registered residents)	8.745	0.262	8.059	9.045
Wage Level	ln (average salary)	11.39	0.127	11.17	11.62

2.3. Model Specification

2.3.1 Baseline model

To examine the effect of digital rural construction on migrant workers' employment quality, the following two-way fixed effects model is constructed:

$$Quality_{ijt} = \alpha_0 + \alpha_1 Digital_{jt} + \alpha_2 \sum CV_{ijt} + pid_i + year_t + \varepsilon_{ijt} \tag{5}$$

Where Q_{ijt} represents the employment quality index of migrant worker i in province j in year t; DE_{jt} is the digital village development level in province j in year t; CV_{ijt} denotes control variables; pid_i and $year_t$ are individual and time fixed effects, respectively; and ε_{ijt} is the error term. The primary coefficient of interest is α_1, which captures the effect of digital village development on employment quality.

2.3.2 Mediating effect model

Based on the preceding analysis, the level of digital village development may influence the employment quality of migrant workers by affecting industrial upgrading and the employment skill structure. To examine these potential mechanisms, the following econometric model is constructed:

$$M_{ijt} = \beta_0 + \beta_1 Digital_{ijt} + \beta_2 \sum CV_{ijt} + pid_i + year_t + \varepsilon_{ijt} \tag{6}$$

$$Quality_{ijt} = \gamma_0 + \gamma_1 M_{ijt} + \gamma_2 \sum CV_{ijt} + pid_i + year_t + \varepsilon_{ijt} \tag{7}$$

where M is the mechanism variables, representing the industrial upgrading *Upgrade* and the employment skill structure *Skill*. Other variables and parameters are defined as in Equation (5).

3. Empirical Analysis

3.1. Baseline regression

The baseline model specified in equation (3) is estimated using heteroskedasticity-robust standard errors to address potential heteroskedasticity. As shown in Table 2, the results indicate that the level of digital village development has a significantly positive effect on the employment quality of migrant workers, regardless of whether control variables are included.The underlying mechanisms may be twofold: first, digital village development activates surplus rural production factors, creates diversified value-added channels, and generates numerous emerging job opportunities with relatively low skill and entry barriers, thereby increasing the likelihood of high-quality employment for migrant workers. Second, by concentrating factor demand and reducing labor market frictions, digital village development alleviates information asymmetries faced by migrant workers, enhances their bargaining power, and ultimately improves overall employment quality.

Table.2. Baseline regression results

Variable	Dependent Variable: *Quality*			
	(1) FE	(2) FE	(3) FE	(4) FE
Digital	0.009^{**} (0.005)	0.009^{***} (0.005)	0.010^{**} (0.005)	0.014^{**} (0.006)
Individual Control	NO	YES	YES	YES
Family Control	NO	NO	YES	YES
Region Control	NO	NO	NO	YES
Individual and Year FE	YES	YES	YES	YES
Constant	0.102^{***} (0.002)	-0.649^{**} (0.288)	-0.638^{**} (0.289)	-0.199 (0.654)
Observations	1292	1292	1292	1292
R^2	0.124	0.151	0.156	0.169

Note: ***, **, and * respectively indicate significance at the 1 %, 5 %, and 10 % levels; values in parentheses are heteroscedasticity robust standard error.

3.2. Robustness test

To verify the reliability of the baseline model results, this study conducts the following robustness test.

3.2.1 Model Substitution

Given that the core explanatory variable—digital village construction—is measured at the provincial level, while the dependent variable—employment quality—is at the individual level, the HLM model is employed to appropriately match micro-level individual data with macro-level regional variables. First, a null model is constructed to test the applicability of HLM. The results show within-group variance $\sigma^2 = 0.0008701$, between-group variance $\pi_{00} = 0.0000748$, and intraclass correlation coefficient $ICC = \pi_{00}/(\pi_{00} + \sigma^2) = 0.0792$. According to Cohen's empirical standards and a likelihood-ratio (LR) test p-value of 0.000, the HLM specification is valid. Additionally, since employment quality is bounded between 0 and 1, representing a censored variable, a Tobit model is also used for robustness testing.

3.2.2 Alternative Measurement of the Dependent Variable

While the original employment quality index was constructed using equal weighting, the entropy weighting method (EWM) and principal component analysis (PCA) are employed to reconstruct the index for robustness.

3.2.3 High-Dimensional Fixed Effects

Considering the heterogeneity in the timing and degree of integration between digital village development and different industries, and the higher job instability and frequent sectoral shifts among migrant workers relative to urban labor, this study introduces "Industry×Year" fixed effects to control for unobserved time- and industry-specific factors.

3.2.4 Sample Optimization

First, to mitigate the influence of outliers due to the wide range of digital village construction levels, this variable is winsorized at the 5th and 95th percentiles. Second, since age and education significantly influence employment quality, the sample is refined by restricting it to prime-age workers (25–55 years) and excluding individuals with extreme educational backgrounds (illiterate or holding master's/doctoral degrees).

The estimation results of these robustness checks are presented in Table 3. The coefficient of digital village construction remains significantly positive at the 5% level or higher across all specifications, confirming the robustness of the main findings.

Table.3. Robustness test results

Variable	Panel A: Model Substitution		Panel B: Alternative Measurement	
	HLM	Tobit	EWM	PCA
Digital	0.008^{**} (0.003)	0.014^{***} (0.004)	0.097^{***} (0.036)	0.049^{**} (0.021)
Constant	0.052^{*} (0.031)	-0.271 (0.645)	-1.320 (5.496)	3.747 (3.081)
Control	YES	YES	YES	YES
Individual and Year FE	YES	YES	YES	YES
Observations	1292	1292	1292	1292
R^2	-	-	0.157	0.046
Variable	Panel C:		Panel D: Sample Optimization	
	High-dimensional fixed effects		Winsorized	Restricted
Digital	0.014^{***} (0.005)		0.014^{**} (0.006)	0.013^{**} (0.005)
Constant	-0.564 (0.728)		-0.199 (0.654)	0.133 (0.652)
Control	YES		YES	YES
Individual FE	YES		YES	YES
Year FE	NO		YES	YES
Industry × Year FE	YES		NO	NO
Observations	1292		1265	947
R^2	0.248		0.169	0.133

3.3. Mechanism test

The mechanism test results are presented in Table 4. The estimated coefficients of digital village construction on both industrial upgrading and employment skill structure are significantly positive, indicating that digital village development facilitates the advancement of industrial structure and the upgrading of employment skills. Furthermore, the coefficients of industrial upgrading and employment skill structure on migrant workers' job quality are also significantly positive, suggesting that digital village construction improves the employment quality of migrant workers by advancing the industrial structure and optimizing the employment skill composition.

3.4. Expansion analysis

To further explore the structural effects of digital rural construction, this paper conducts a comparative analysis of its impact on migrant workers' employment quality from four key dimensions. The results of the two-stage instrumental variable estimation are presented in Table 5. All four components—rural digital infrastructure, rural digital economy, rural digital governance, and rural digital life—exert significantly positive effects on migrant workers' employment quality. Among them, the impact of rural digital life is the most pronounced, followed by the rural digital economy, digital infrastructure, and digital governance. A plausible explanation is that although the penetration of digital infrastructure such as the internet has improved in rural areas, an "application gap" persists. The development of digital life in rural areas addresses shortcomings in the application of digital technologies to consumption, tourism, and life services, thereby more directly enhancing employment quality for migrant workers [10].

Table.4. Mechanism test results

Variable	Industrial structure upgrading		Employment skill structure	
	Upgrade	Quality	Skill	Quality
Digital	0.068^{***} (0.009)		0.038^{***} (0.004)	
Upgrade		0.203^{**} (0.082)		
Skill				0.363^{**} (0.147)
Constant	-0.936 (1.489)	-0.009 (0.693)	1.269^{**} (0.541)	-0.661 (0.589)
Control	YES	YES	YES	YES
Individual and Year FE	YES	YES	YES	YES
Observations	1292	1292	1292	1292
R^2	0.537	0.169	0.909	0.169

Table.5. Expansion analysis results

Variable	Dependent Variable: Quality			
	(1) IV-2SLS	(2) IV-2SLS	(3) IV-2SLS	(4) IV-2SLS
Infrastructure	0.027^{**} (0.017)			
Economy		0.035^{**} (0.015)		
Governance			0.020^{**} (0.008)	
Life				0.046^{**} (0.022)
Control	YES	YES	YES	YES
Individual and Year FE	YES	YES	YES	YES
Observations	1238	1238	1238	1238
R^2	0.156	0.162	0.142	0.127

4. Conclusions

This paper empirically investigates the impact of digital rural construction on the employment quality of migrant workers by matching the 2018 and 2020 China Family Panel Studies (CFPS) with the county-level Digital Village Index. It further explores the underlying mechanisms through the lenses of industrial upgrading and the employment skill structure. The key findings are as follows: First, digital village development significantly enhances the employment quality of migrant workers, a result that remains robust after addressing endogeneity concerns and conducting a series of robustness checks. Second, digital village initiatives improve employment quality by promoting industrial structure upgrading and increasing the share of high-skilled labor in the employment structure. Third, the dimensional analysis reveals that rural digital economy exerts the greatest positive effect, followed by rural digital life, rural digital infrastructure, and rural digital governance.

Despite providing robust empirical evidence on the positive impact of digital village construction on migrant workers' job quality, this study still faces several limitations. First, due to data constraints, the digital village index is measured at the provincial level, which may obscure intra-regional heterogeneity. Future research could leverage higher-resolution spatial data and employ spatial econometric models to explore spillover effects and cross-regional dynamics. Second, this paper primarily focuses on structural and skill-based mechanisms; future research could examine how digital villages reshape social capital, trust in digital platforms, or labor market matching efficiency. Finally, with emerging technologies such as AI, blockchain, and IoT increasingly embedded in rural development, it is crucial to explore how algorithmic governance and datafication are reshaping rural employment ecology. These directions will enrich the theoretical framework and policy implications of digital rural transformation.

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