Research Article

Influence of Digital Finance on Efficacy of Entrepreneurship by Returning Migrant Workers

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Digital finance provides an ideal entrepreneurial environment for returning migrant workers (RMWs). From the perspective of entrepreneurs, many scholars have quantified the factors affecting entrepreneurship, as well as the entrepreneurial environment, theorized the importance, motives, and internal/external impactors of RMW entrepreneurship, and put forward quite a lot of countermeasures. This paper innovatively evaluates how digital finance influences the efficacy of RMW entrepreneurship. Firstly, the authors established an influencing factor analysis model and an RMW entrepreneurship model and explained principles for the structural equation modeling of the influence of digital finance on RMW entrepreneurship efficacy. Next, the traditional partial least squares (PLS) regression was optimized, the optimal initial iteration values (IIVs) were obtained, and the algorithm convergence was achieved. Finally, a multilayer structural equation model (SEM) was constructed to evaluate the influence of digital finance on RMW entrepreneurship efficacy. The proposed algorithm and model were proved valid and feasible through experiments.

1. Introduction

China has entered the new era of mass entrepreneurship and innovation. Effective entrepreneurial activities are the foundation of national development and an important aspect of building a well-off society. Returning migrant workers (RMWs), i.e., the migrant workers returning from cities to their hometowns form a large group of potential entrepreneurs and have a rather large need to start their own businesses.

RMW entrepreneurship provides an effective solution to the economic problems of RMWs and creates more job opportunities for rural surplus labor [1–4]. By promoting rural economy, RMW entrepreneurship contributes to the construction of new socialist countryside, which is advocated by the Chinese government [5–7].

Free from the shackles of physical financial outlets, digital finance, with a low marginal cost, offers an ideal entrepreneurial environment for RMWs. To fuel the success and enthusiasm of RMW entrepreneurship, it is particularly important to sort out the effects of digital finance on RMW entrepreneurship.

Since the birth of the strategy of rural vitalization, China and the Chinese society have attached great importance to RMW entrepreneurship [8–10]. Ferreira et al. [11] carried a field survey on the relationship between rural revitalization and the local employment of rural surplus labor, constructed a binary logistic regression model, and carried out an SPSS-based analysis on the efficacy of RMW entrepreneurship under different changing factors, including age, gender, family background, local policy support, and regional economic level.

It is of certain practical significance to study the obstacles to RMW entrepreneurship [12–14]. Santoro et al. [15] divided these obstacles into network obstacles and policy obstacles, tested these factors through Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity, and extracted 21 principal components. Ferreras-Méndez et al. [16] summarized the obstacles to RMW entrepreneurship through interpretive structural modeling (ISM) and decision-making

trail and evaluation laboratory (DEMATEL) and divided five classes of core obstacles into different layers. Castellano et al. [17] designed a backpropagation neural network (BPNN) to predict the number of RMW entrepreneurs and forecasted that number in 2015–2020 with self-designed test set and training set.

The advancement of social informatization and proliferation of Internet finance have spurred the development of rural economy. But there is not yet a mature information platform or network system. In the field of rural revitalization, many researchers are interested in how modern digital finance information platform supports the flexible, adaptive, and continuous development of largescale RMW entrepreneurship [18–20]. Khalid [21] deeply explored the influence of rural digital finance informatization on RMW entrepreneurship and described the ideas and countermeasures for building a reasonable service system of rural digital finance informatization.

Combined with national conditions, most studies focus on analyzing the factors affecting entrepreneurship from the perspective of entrepreneurs and qualifying the entrepreneurial environment. There are many theoretical analyses on the importance, motivation, and internal/external impactors of RMW entrepreneurship, leading to numerous countermeasures and suggestions [22–26].

Digital finance is a simple, low-cost, highly collaborative technology that facilitates interaction and communication. Considering the boom of digital finance in China, this paper introduces the technology to evaluate the efficacy of RMW entrepreneurship. The main contents are as follows: (1) setting up an influencing factor analysis model and an RMW entrepreneurship model and explaining the principles for the structural equation modeling of the influence of digital finance on RMW entrepreneurship efficacy; (2) optimizing the traditional partial least squares (PLS) regression to overcome the problem with model parameter estimation, solving the optimal initial iteration values (IIVs) under the constraints of reasonable least squares sense and unit vector length, and presenting the idea of algorithm convergence; (3) building a multilayer structural equation model (SEM) to evaluate the influence of digital finance on RMW entrepreneurship efficacy. The proposed algorithm and model were proved valid and feasible through experiments.

2. Principles of Structural Equation Modeling

By the causes of behaviors, this paper divides the factors affecting RMW entrepreneurship in the context of digital finance into external factors and internal factors. According to the influencing factor analysis model in Figure 1, the internal dimension includes education level, personal quality, interpersonal network, and other personal factors of RMWs, while the external dimension covers three aspects: policy supports of digital finance, macro environment of market economy, and social service environment.

Next, an RMW entrepreneurship model was constructed (Figure 2). The model separates the RMW entrepreneurship process into multiple phases: generating entrepreneurship motives, identifying entrepreneurial opportunities, making
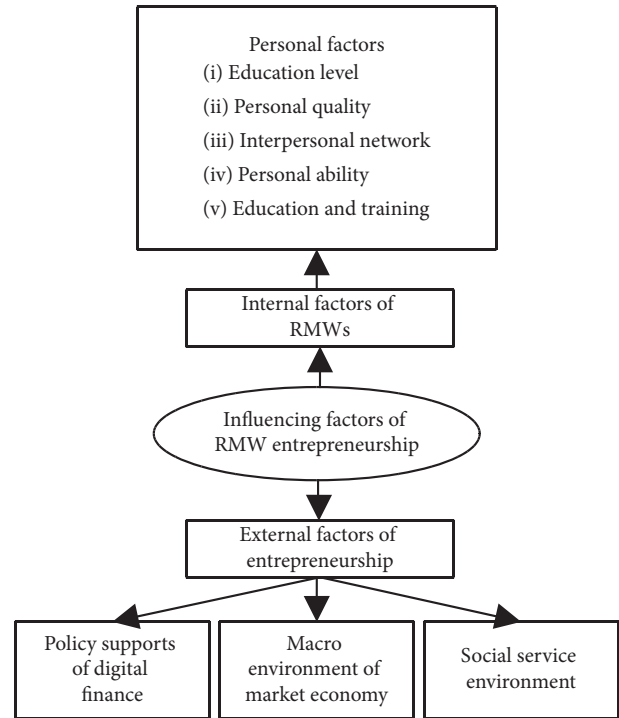

FIGURE 1: Influencing factor analysis model.

entrepreneurial decisions, acquiring entrepreneurial resources, and delivering entrepreneurial results. However, some digital finance factors affecting the implementation of RMW entrepreneurship cannot be measured directly, but be characterized indirectly with measurable indices. These factors include regional entrepreneurial atmosphere, digital finance network embedding, and cognitive embedding. Specifically, the creation of entrepreneurial atmosphere, digital finance network embedding, and digital finance model can be characterized by the degree of digital finance operation that of digital marketing and that of digital finance services; the cognitive embedding can be characterized by the willingness, motivation, and decision of entrepreneurship. If the variation in RMW entrepreneurship efficacy only brings changes to the scale of entrepreneurial assets, which is directly measurable, then the measured scale of entrepreneurial assets can be used as a yardstick of the variation in RMW entrepreneurship efficacy. As a result, the SEM with latent variables becomes increasingly popular in the fields of corporate performance and entrepreneurial behavior.

This paper intends to evaluate the influence of digital finance on the efficacy of RMW entrepreneurship. According to the incubation model of RMW entrepreneurship (Figure 3), the RMW entrepreneurship covers multiple stages, such as generation of entrepreneurial motives, identification of entrepreneurial opportunities, making of entrepreneurial decisions, acquisition of entrepreneurial resources, and delivery of initial entrepreneurial results. The model is a multilayer statistical analysis tool containing multiple latent and observable variables. It is extremely difficult to estimate the model parameters. Relying on the overall variation, PLS regression provides a suitable tool to
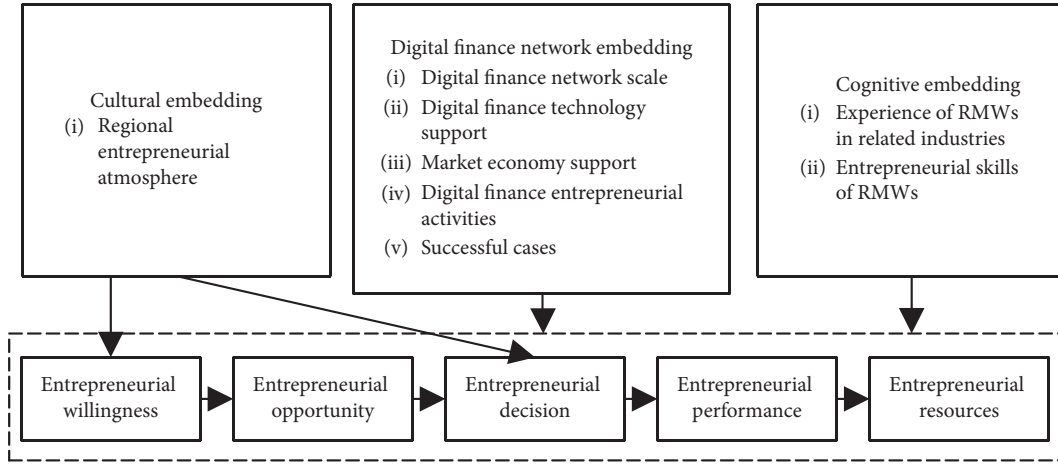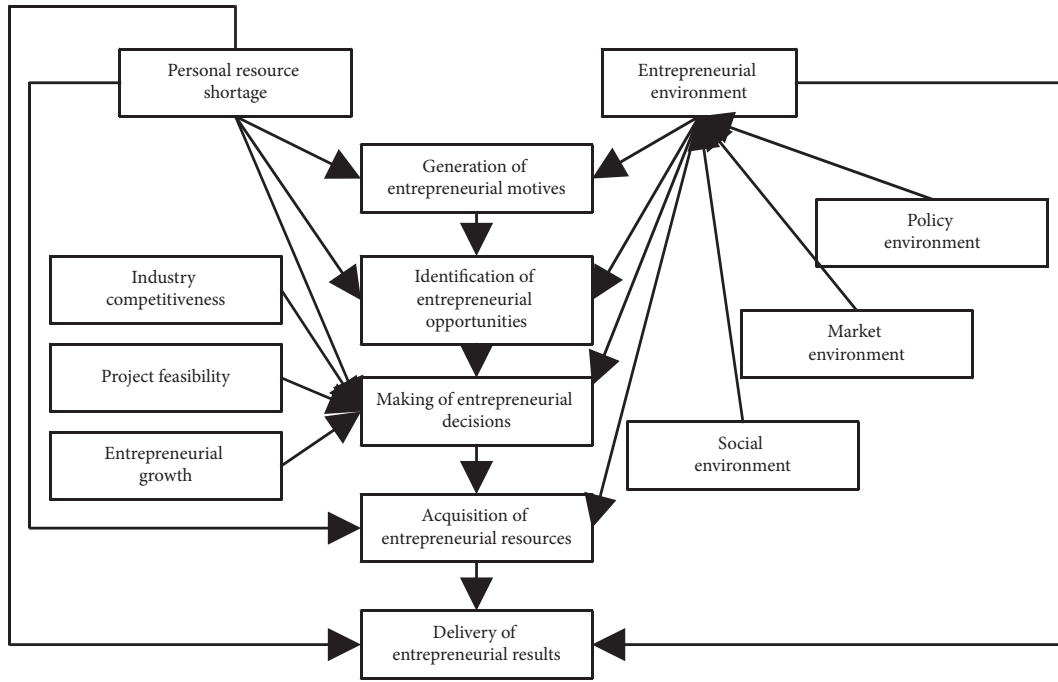
Figure 2: RMW entrepreneurship model.

Figure 3: Incubation model of RMW entrepreneurship.

handle complex SEMs, with no strict requirements on the distribution of observations or the number of samples.

To disclose the influence of digital finance on RMW entrepreneurship efficacy, this paper constructs a causality-based SEM to estimate the degree of the said influence. Let $\beta = (\beta_1, \ldots, \beta_n)^T$ and $\delta = (\delta_1, \ldots, \delta_l)^T$ be the n endogenous latent variables and l exogenous latent variables of the SEM, respectively; $ZH_{n \times n}$ be the factor loading matrix of β; $\Theta_{n \times l}$ be the factor loading matrix of δ; and $\sigma_\beta = (\sigma_{\beta 1}, \ldots, \sigma_{\beta n})^T$ be the residual. Then, the relationship between the latent variables of the model can be described by

$$\beta = ZH \cdot \beta + \Theta \cdot \delta + \sigma_\beta. \tag{1}$$

The measured variables of the SEM can indirectly characterize the latent variables. Suppose the SEM contains N measured variables, which measure M samples for M times. Then, the measured data can be compiled into an $M \times N$ matrix. Let a_{ij} and b_{ij} be the measured variables related to δ_τ and β_i, respectively; $\Phi_{\tau j}$ be the aggregation coefficient from measured variables to exogenous latent variables; and $\sigma_{\delta \tau}$ be the corresponding error term. Then, the relationship between the exogenous latent variables and measured variables can be described by

$$\delta_\tau = \sum_{j=1}^{L(\tau)} \Phi_{ij} a_{ij} + \sigma_{\varepsilon t}, \quad \tau = 1, \ldots, l, j = 1, \ldots, L(\tau). \tag{2}$$

Let ζ_{ij} be the aggregation coefficient from measured variables to endogenous latent variables and $\sigma_{\beta i}$ be the corresponding error term. Then, the relationship between the endogenous latent variables and measured variables can be described by

$$\beta_i = \sum_{j=1}^{K(i)} \zeta_{ij} b_{ij} + \sigma_{\beta i}, \quad i = 1, \ldots, n, j = 1, \ldots, K(i). \quad (3)$$

Suppose $a_\tau = (a_{i1}, \ldots, x_{iL(\tau)})^T$, $b_i = (b_{i1}, \ldots, b_{iK(i)})^T$, $\Phi_\tau = (\Phi_{i1}, \ldots, \Phi_{iL(\tau)})^T$, and $\zeta_i = (\zeta_{i1}, \ldots, \zeta_{iK(\tau)})^T$. Then, formula (2) can be rewritten in a general form:

$$\delta_\tau = \Phi_\tau^T a_\tau + \sigma_{\delta_\tau}, \quad \tau = 1, \ldots, l. \quad (4)$$

Formula (3) can also be rewritten in a general form:

$$\beta_i = \zeta_\tau^T b_i + \sigma_{\beta_i}, \quad i = 1, \ldots, n. \quad (5)$$

By reverse thinking, the variation in a measured variable of the SEM is driven by the changes of the corresponding latent variable. Let θ_{ij} and $\sigma_{\delta\tau j}$ be the loading coefficient and error term from latent variables to endogenous measured variables, respectively. Then, we have

$$\begin{pmatrix} a_{\tau 1} \\ \vdots \\ a_{\tau L(\tau)} \end{pmatrix} = \begin{pmatrix} \theta_{\tau 1} \\ \vdots \\ \theta_{\tau L(\tau)} \end{pmatrix} \delta_\tau + \begin{pmatrix} \sigma_{a\tau 1} \\ \vdots \\ \sigma_{a\tau L(\tau)} \end{pmatrix}, \quad \tau = 1, \ldots, l. \quad (6)$$

Let μ_{ij} and $\sigma_{\beta ij}$ be the loading coefficient and error term from latent variables to exogenous measured variables, respectively. Then, we have

$$\begin{pmatrix} b_{i1} \\ \vdots \\ b_{iK(i)} \end{pmatrix} = \begin{pmatrix} \mu_{i1} \\ \vdots \\ \mu_{iK(i)} \end{pmatrix} \beta_i + \begin{pmatrix} \sigma_{bi1} \\ \vdots \\ \sigma_{biK(i)} \end{pmatrix}, \quad i = 1, \ldots, n. \quad (7)$$

Suppose $\theta_\tau = (\theta_{i1}, \ldots, \theta_{iL(\tau)})^T, \mu_i = (\mu_{i1}, \ldots, \mu_{iK(i)})^T$. Then, formulas (6) and (7) can be rewritten in a general form:

$$a_\tau = \theta_\tau \delta_\tau + \sigma_{a_\tau}, \quad \tau = 1, \ldots, l, \quad (8)$$

$$b_i = \mu_i \beta_i + \sigma_{b_i}, \quad i = 1, \ldots, n. \quad (9)$$

Combining formulas (1), (4), and (5), a formative SEM with forward measurements can be established:

$$\Omega_{\text{SEM}}^+ = \begin{cases} \beta = ZH \cdot \beta + \Theta \cdot \delta + \sigma_\beta, \\ \delta_\tau = \Phi_\tau^T a_\tau + \sigma_{\delta_\tau}, \tau = 1, \ldots, l, \\ \beta_i = \zeta_\tau^T b_i + \sigma_{\beta_i}, \quad i = 1, \ldots, n. \end{cases} \quad (10)$$

Combining formulas (1), (8), and (9), a reflective SEM with reverse measurements can be obtained as

$$\Omega_{\text{SEM}}^- = \begin{cases} \beta = ZH \cdot \beta + \Theta \cdot \delta + \sigma_\beta, \\ a_\tau = \theta_\tau \delta_\tau + \sigma_{a_\tau}, \quad \tau = 1, \ldots, l, \\ b_i = \mu_i \beta_i + \sigma_{b_i}, \quad i = 1, \ldots, n. \end{cases} \quad (11)$$

Traditionally, SEM parameters are solved through PLS regression. The specific iterative process of this approach can be expressed as

$$\left(\Phi_{\tau j}, \zeta_{ij}\right)^{(0)} \xrightarrow{(2)(3)} \left(\delta_\tau', \beta_i'\right)^{(0)} \xrightarrow{(1)} \left(\eta_{\tau j}, \gamma_{ij}\right)^{(0)} \xrightarrow{(1)} \left(\delta_\tau'', \beta_i'\right)^{(2)(3)} \left(\Phi_{\tau j}, \zeta_{ij}\right)^{(1)}. \quad (12)$$

However, the PLS regression algorithm often fails to converge to a suitable solution, owing to the randomness of IIVs. The IIVs must be selected suitably to ensure algorithm convergence.

3. IIV Optimization and Algorithm Convergence

The traditional PLS regression proceeds with the IIVs randomly set by formulas (2) and (3). Here, the IIVs are optimized by formulas (6) and (7) or formulas (8) and (9) for the indeterminate SEM, under the constraints of reasonable

least squares sense and unit vector length. For the measured variable $a_\tau = (a_{i1}, \ldots, a_{iL(\tau)})^T$, any component $a_{\tau i}$ is involved in M measurements $a_{\tau j}=(a_{ij1}, \ldots, a_{ijM})$. By right multiplication of a_τ^T, formula (8) can be converted into

$$a_\tau a_\tau^T \approx \theta_\tau \delta_\tau \delta_\tau^T \theta_\tau^T = \delta_\tau \delta_\tau^T \theta_\tau \theta_\tau^T. \quad (13)$$

Suppose latent variable δ_τ is a unit vector satisfying $\delta_\tau \delta_\tau^T = 1$. Then, we have

$$a_\tau a_\tau^T \approx \theta_\tau \theta_\tau^T. \quad (14)$$

Formula (14) can be expanded into

$$\begin{pmatrix} x_{t1} x_{t1}^T & a_{\tau 1} a_{\tau 2}^T & \cdots & a_{\tau 1} a_{\tau L(\tau)}^T \\ x_{t2} x_{t1}^T & a_{\tau 2} a_{\tau 2}^T & \cdots & a_{\tau 2} a_{\tau L(\tau)}^T \\ \cdots & \cdots & \cdots & \cdots \\ a_{\tau L(\tau)} a_{\tau 1}^T & a_{\tau L(\tau)} a_{\tau 2}^T & \cdots & a_{\tau L(\tau)} x_{\tau L(\tau)}^T \end{pmatrix} \approx \begin{pmatrix} \theta_{\tau 1}^2 & \theta_{\tau 1} \theta_{\tau 2} & \cdots & \theta_{\tau 2} \theta_{\tau L(\tau)} \\ \theta_{\tau 2} \theta_{\tau 1} & \theta_{\tau 2}^2 & \cdots & \theta_{\tau 2} \theta_{\tau L(\tau)} \\ \cdots & \cdots & \cdots & \cdots \\ \theta_{\tau L(\tau)} \theta_{\tau 1} & \theta_{\tau L(\tau)} \theta_{\tau 2} & \cdots & \theta_{\tau L(\tau)}^2 \end{pmatrix}. \quad (15)$$

In the left matrix, every element $a_{\tau j} a_{\tau j}^T$ is a product of vectors; in the right matrix, every element $\theta_{\tau j} \theta_{\tau j}^T$ is a product of numbers. The corresponding diagonal elements of the two matrices are equal. Hence, we have

$$\theta_{\tau j}^2 = a_{\tau j} a_{\tau j}^T, \quad j = 1, \ldots, L(\tau). \tag{16}$$

By formula (16), the loading coefficient θ_τ can be estimated as $\theta_\tau' = (\theta_\tau', \ldots, \theta_{\tau L(\tau)}')^T$. The estimation of θ_τ is biased, because the variance of the error term is ignored. Thus, the parameter estimation needs to be optimized to eliminate the bias. Suppose δ_τ and $\sigma_{a\tau}$ are independent of each other, and $CM(\sigma_{a\tau}) = 0$. Then, there exists an equation $CM(\delta_\tau \sigma_{a\tau}) = CM(\delta_\tau) CM(\sigma_{a\tau}) = 0$. Let $CM(\sigma_{a\tau}, \sigma_{a\tau}^T)$ be the covariance matrix $\sum \sigma_{a\tau}$ of error vector $\sigma_{a\tau}$. Then, formula (8) can be converted into

$$\begin{aligned} CM(a_\tau a_\tau^T) &= CM\left[(\theta_\tau \delta_\tau + \sigma_{a\tau})(\delta_\tau^T \theta_\tau^T + \sigma_{a\tau}^T)\right] \\ &= CM(\theta_\tau \delta_\tau \delta_\tau^T \theta_\tau^T) + CM(\theta_\tau \delta_\tau \theta_\tau^T) \\ &\quad + CM(\sigma_{a\tau} \delta_\tau^T \theta_\tau^T) + CM(\sigma_{a\tau} \sigma_{a\tau}^T) \\ &= CM(\theta_\tau \theta_\tau^T) + CM(\sigma_{a\tau} \sigma_{a\tau}^T) \\ &= \theta_\tau \theta_\tau^T + CM(\sigma_{a\tau} \sigma_{a\tau}^T). \end{aligned} \tag{17}$$

Since the diagonal elements of the symmetric matrix $\sum \sigma_{a\tau}$ are the variances in different dimensions, we have

$$\begin{aligned} CM(\sigma_{a\tau} \sigma_{a\tau}^T) &= \mathrm{Var}(\sigma_{a\tau}) \\ &= \sum \sigma_{a\tau} = \mathrm{diag}\left(\phi_{a\tau1}^2, \phi_{a\tau2}^2, \ldots, \phi_{a\tau L(\tau)}^2\right). \end{aligned} \tag{18}$$

Comparing with the diagonal elements in matrix 14, we have

$$a_{\tau j} a_{\tau j}^T = \theta_{\tau j}^2 + \phi_{\tau j}^2, \quad j = 1, \ldots, L(\tau). \tag{19}$$

To solve formula (19), the first step is to solve $\varphi_{ij}'^2$. Suppose $CM(a_\tau) = 0$, $\Sigma_{a\tau} = CM(a_\tau a_\tau^T)$, and $\Sigma_{a\tau}^{-1}$ exists. Let $\lambda_{a\tau}'$ be a diagonal element of $\Sigma_{a\tau}'$. Drawing on factor analysis, φ_{ij}^2 can be estimated by

$$\lambda_{a\tau j}' = \phi_{a\tau j}'^2, \quad j = 1, \ldots, L(\tau). \tag{20}$$

Combining formulas (19) and (20),

$$\theta_{\tau j}^2 = a_{\tau j} a_{\tau j}^T - \lambda_{a\tau j}', \quad j = 1, \ldots, L(\tau). \tag{21}$$

Similarly, θ_{ij}^2 can be solved. Finally, it is necessary to estimate latent variable $\delta\tau$. Suppose $\delta_\tau = (\delta_{\tau1}, \delta_{\tau2}, \ldots, \delta_{\tau M})^T$. Then, the W-th component of δ_τ can be expressed as

$$\begin{pmatrix} a_{\tau 1 W} \\ \vdots \\ a_{\tau L(\tau) W} \end{pmatrix} = \begin{pmatrix} \theta_{\tau 1} \\ \vdots \\ \theta_{\tau L(\tau)} \end{pmatrix} \delta_{\tau W} + \begin{pmatrix} \sigma_{a\tau 1} \\ \vdots \\ \sigma_{a\tau L(\tau)} \end{pmatrix}, \quad \tau = 1, \ldots, l, W = 1, \ldots, M. \tag{22}$$

By left multiplication of θ_τ^T, formula (22) can be converted into

$$\left(\theta_{\tau 1}, \ldots, \theta_{\tau L(\tau)}\right) \begin{pmatrix} a_{\tau 1 W} \\ \vdots \\ a_{\tau L(\tau) W} \end{pmatrix} = \sum_{j=1}^{L(\tau)} \theta_{\tau j}^2 \delta_{\tau W} + \theta_\tau^T \begin{pmatrix} \sigma_{a\tau 1} \\ \vdots \\ \sigma_{a\tau L(\tau)} \end{pmatrix}, \tag{23}$$

where $\theta_{\tau j}'$ characterizes the influence of $\sigma_{a\tau}$ on a_τ. Then, formula (23) can be improved by the least squares principle:

$$\left(\theta_{\tau j}', \ldots, \theta_{\tau L(t)}'\right) \begin{pmatrix} a_{\tau 1 W} \\ \vdots \\ a_{\tau L(\tau) W} \end{pmatrix} = \sum_{j=1}^{L(\tau)} \theta_{\tau j}^2 \delta_{\tau W}. \tag{24}$$

Then, $\delta_{\tau W}$ can be estimated by

$$\delta_{\tau W}' = \frac{\theta_{\tau 1}'}{D} a_{\tau 1 W} + \ldots + \frac{\theta_{\tau L(\tau)}'}{D} a_{\tau L(\tau) W}, \quad W = 1, \ldots, M, D = \theta_\tau'^T \theta_\tau'. \tag{25}$$

The estimated value of $\Phi_{\tau j}$ can be obtained by substituting the estimated δ_τ into formula (2). By the same method, the other parameters can be computed, namely,

μ_{ij}', β_i' and ζ_{ij}. In other words, the optimal IIVs for the PLS regression under the constraint of unit vector length satisfy

$$\left\| \delta_\tau - \sum_{j=1}^{L(\tau)} \Phi_{\tau j} a_{\tau j} \right\| \longrightarrow \min. \tag{26}$$

The following is a discussion of the convergence of the PLS regression with optimal IIVs. Formula (1) can be converted into

$$(I - ZH)\beta = \Theta \cdot \delta + \sigma_\beta. \tag{27}$$

In the evaluation model for the influence of digital finance on RMW entrepreneurship efficacy, matrices ZH and $ZH_\tau = I - ZH$ are both triangular matrices, where the sum of diagonal elements equals 0. Besides, $|ZH_\tau| = 1$, and ZH_τ^{-1} exists. Then, we have

$$\beta = ZH_F^{-1} \cdot \Theta \cdot \delta + ZH_F^{-1} \sigma_\beta = ZH_\Theta \cdot \delta + \sigma_H, \tag{28}$$

where $ZH_\Theta = ZH_F^{-1}$; $\sigma_H = ZH_F^{-1} \cdot \sigma_\beta$. If the PLS solutions to latent variables δ and β are obtained under the constraint, it is possible to find the PLS solutions to the factor loading matrices ZH and Θ. If the PLS solution of formula (28) is directly iterated without being unitized, then $\|\beta_i'\| \le \|\beta_i\| = 1$.

In this case, it is necessary to verify the convergence of the PLS regression. Expanding the i-th component of the PLS solution,

$$\beta_i = \sum_{j=1}^{U(i)} H_{\Theta ij}\delta_j + \sigma_{Hi}, \quad i = 1,\ldots,n, j = 1,\ldots,l. \quad (29)$$

Let $U(i)$ be the number of δ_j related to β_i. Then, the least squares sense of formula (29) can be described by

$$\left\| \sum_{g=1}^{K(i)} \zeta_{if}b_{if} - \sum_{j=1}^{U(i)} H_{\Theta ij} \sum_{t=1}^{L(j)} \Phi_{jt}a_{jt} \right\| \longrightarrow \min, \quad i = 1,\ldots,n, g = 1,\ldots,K(i), j = 1,\ldots,l, t = 1,\ldots,L(j). \quad (31)$$

Formula (31) is equivalent to the mutual projections of two unconstrained subspaces. Thus, the solution to the formula approximates the minimum of zero. Therefore, the improved PLS regression can converge iteratively through the control of any parameter error.

4. SEM for Influence of Digital Finance on RMW Entrepreneurship Efficacy

In traditional SEM, latent variables are directly connected with measured variables via a single layer of paths. Considering the complexity of RMW entrepreneurship process, this paper constructs a multilayer statistical model containing multiple latent and observable variables. Figure 4 presents the evaluation model for the influence of digital finance on RMW entrepreneurship efficacy.

Our evaluation model contains 29 observable variables. The eight latent variables, namely, digital operation δ_1, digital marketing δ_2, digital finance services δ_3, entrepreneurial motives β_1, entrepreneurial willingness β_2, entrepreneurial foundation β_3, entrepreneurial decisions β_4, and entrepreneurial performance β_5, correspond to 6, 3, 2, 0, 5, 6, 4, and 3 measured variables, respectively.

Let $a_{\tau j}$ be the measured variable corresponding to an exogenous latent variable of the model. Then, the measurement equation between exogenous latent variables and measured variables can be established as

$$\begin{pmatrix} a_{\tau 1} \\ \vdots \\ a_{\tau L(\tau)} \end{pmatrix} = \begin{pmatrix} \theta_{\tau 1} \\ \vdots \\ \theta_{\tau L(\tau)} \end{pmatrix} \delta_\tau + \begin{pmatrix} \sigma_{a\tau 1} \\ \vdots \\ \sigma_{a\tau L(\tau)} \end{pmatrix}. \quad (32)$$

Let $\theta_{\tau j}$ be the loading coefficient between the τ-th exogenous latent variable and the j-th measured variable and $\sigma_{a\tau j}$ be the error corresponding to the j-th measured variable of the τ-th exogenous latent variable. Then, formula (23) can be expanded into

$$\left\| \beta_\tau - \sum_{j=1}^{U(i)} H_{\Theta ij}\delta_j \right\| \longrightarrow \min, \quad i = 1,\ldots,n, j = 1,\ldots,l. \quad (30)$$

Combining formula (30) with formulas (2) and (3),

$$\begin{pmatrix} a_{11} \\ \vdots \\ a_{16} \\ a_{21} \\ \vdots \\ a_{23} \\ a_{31} \\ \vdots \\ a_{32} \end{pmatrix} = \begin{pmatrix} \theta_{11} & 0 & 0 \\ \vdots & \vdots & \vdots \\ \theta_{16} & 0 & 0 \\ 0 & \theta_{21} & 0 \\ \vdots & \vdots & \vdots \\ 0 & \theta_{23} & 0 \\ 0 & 0 & \theta_{31} \\ \vdots & \vdots & \vdots \\ 0 & 0 & \theta_{32} \end{pmatrix} \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{pmatrix} + \begin{pmatrix} \sigma_{a_{11}} \\ \vdots \\ \sigma_{a_{16}} \\ \sigma_{a_{21}} \\ \vdots \\ \sigma_{a_{23}} \\ \sigma_{a_{31}} \\ \vdots \\ \sigma_{a_{32}} \end{pmatrix}. \quad (33)$$

Let θ_{ij} be the measured variable corresponding to an endogenous latent variable of the model. Then, the measurement equation between endogenous latent variables and measured variables can be established as

$$\begin{pmatrix} b_{i1} \\ \vdots \\ b_{iL(i)} \end{pmatrix} = \begin{pmatrix} \mu_{i1} \\ \vdots \\ \mu_{iL(i)} \end{pmatrix} \delta_\tau + \begin{pmatrix} \sigma_{bi1} \\ \vdots \\ \sigma_{biL(i)} \end{pmatrix}. \quad (34)$$

Let μ_{ij} be the loading coefficient between the i-th endogenous latent variable and the j-th measured variable and $\sigma_{b\tau j}$ be the error corresponding to the j-th measured variable of the i-th endogenous latent variable. Then, formula (34) can be expanded into

$$\begin{pmatrix} b_{21} \\ \vdots \\ b_{25} \\ b_{31} \\ \vdots \\ b_{36} \\ b_{41} \\ \vdots \\ b_{44} \\ b_{51} \\ \vdots \\ b_{53} \end{pmatrix} = \begin{pmatrix} 0 & \mu_{21} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \mu_{25} & 0 & 0 & 0 \\ 0 & 0 & \mu_{31} & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \mu_{36} & 0 & 0 \\ 0 & 0 & 0 & \mu_{41} & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \mu_{44} & 0 \\ 0 & 0 & 0 & 0 & \mu_{51} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \mu_{53} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{pmatrix} + \begin{pmatrix} \sigma_{b21} \\ \vdots \\ \sigma_{b25} \\ \sigma_{b31} \\ \vdots \\ \sigma_{b36} \\ \sigma_{b41} \\ \vdots \\ \sigma_{b44} \\ \sigma_{b51} \\ \vdots \\ \sigma_{b53} \end{pmatrix}. \quad (35)$$

Figure 4: Evaluation model.
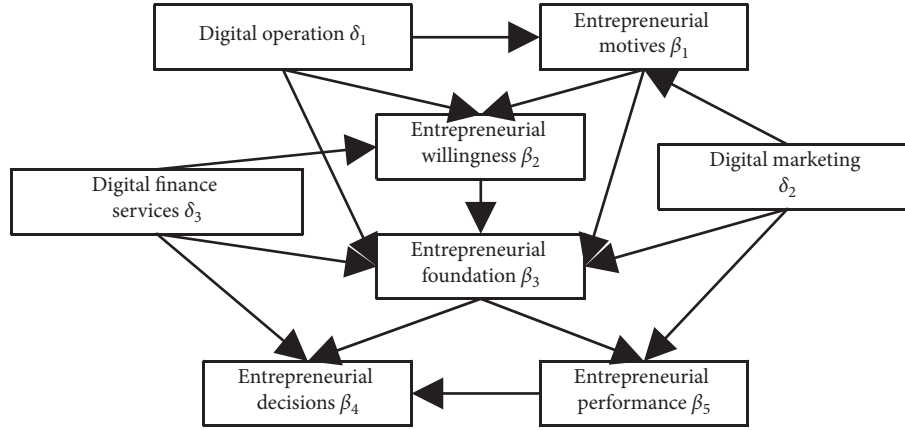
Figure 5 shows the paths of the evaluation model. Let ω_{12} and ω_{13} be the paths from δ_2 and δ_3 to β_1, respectively, and $\omega(\omega_{12}, \omega_{13})^T$. Then, a structural equation can be established for a high-level variable β_1 not connected to any measured variable:

$$\begin{pmatrix} \delta_2 \\ \delta_3 \end{pmatrix} = \begin{pmatrix} \omega_{12} \\ \omega_{13} \end{pmatrix} \beta_1 + \begin{pmatrix} \sigma_{\delta_2} \\ \sigma_{\delta_3} \end{pmatrix}. \qquad (36)$$

Based on the least squares sense, the optimal IIVs can be solved for $\theta_{\tau j}$, μ_{ij}, β_i, δ_i, and $\eta_{\tau j}$. Substituting the IIVs of β_i and δ_i into the basic SEM, it is possible to solve ω, γ_{ij}, and μ_{ij}. Further, the β_i estimates could be derived for low-level and high-level endogenous latent variables. Let ζ_{ij} and ζ_{ij}^* be aggregation coefficients; $K(i)$ be the number of measured variables corresponding to the i-th low-level endogenous latent variable; and $V(i)$ be the number of exogenous latent variables corresponding to the i-th high-level endogenous latent variable. Then, low-level endogenous latent variables could be linked up with measured variables based on the β_i estimates. Then, the structural equation based on the least squares sense can be given by

$$\beta_i = \sum_{j=1}^{K(i)} \zeta_{ij} b_{ij}, \quad i = 2, 3, 4, 5. \qquad (37)$$

Let b_{ij} be the measured variable corresponding to an endogenous variable of the model. Each endogenous latent variable is linked with each measured variable via loading coefficient and error. Then, the relationship between the two values can be measured by

$$\beta_i = \sum_{j=1}^{V(i)} \widetilde{\zeta}_{ij} \delta_j, \quad i = 1. \qquad (38)$$

Then, the aggregation coefficients can be solved by formulas (37) and (38).

5. Experiments and Results Analysis

The RMW entrepreneurship samples under the effect of digital finance were collected through a questionnaire survey. After normalization, the collected data were separately processed by the traditional PLS regression and our improved PLS regression, aiming to disclose the relationship between the latent variables in our evaluation model. Tables 1 and 2 present the estimates of the latent variables and their coefficient relationship. Tables 3 and 4 provide the calculation results of endogenous and exogenous variables under optimal IIVs and random IIVs, respectively. The insignificant difference between the results of the two algorithms suggests the effectiveness of our algorithm. The improved PLS regression, which introduces the optimal IIVs to the traditional PLS regression, could obtain the path coefficients between all variables and calculate the influence coefficient of all measured variables for RMW entrepreneurship under the effect of digital finance. The digital finance impacts on RMW entrepreneurship efficacy could be ranked clearly by our method. The results of our method are more accurate than the traditional PLS regression.

Table 5 shows the cumulative variances of inputs and outputs in RMW entrepreneurship. It can be inferred that five variances can explain 82.53% of all information. Comparing the paths between latent variables, five core variables, including fixed asset investment, equipment rent, research fund, human resources investment, and digital finance platform operation cost, greatly affect the state of latent variables. These core variables promote every phase of RMW entrepreneurship, such as identifying entrepreneurial motives and laying entrepreneurial foundation.

Table 6 shows the cumulative variances of inputs and outputs in policy supports of digital finance. It can be inferred that five variances can explain 84.94% of all information. Comparing the paths between latent variables, five core variables, namely, fiscal support, implementation of policy supports, protection of intellectual property rights, openness of policy supports, and coverage of policy supports, greatly affect the state of latent variables. These core variables promote the entrepreneurial environment.

Table 7 shows the cumulative variances of inputs and outputs in third-party digital finance service providers. It can be inferred that six variances can explain 87.52% of all information. Comparing the paths between latent variables, six core variables, namely, precision financial services,
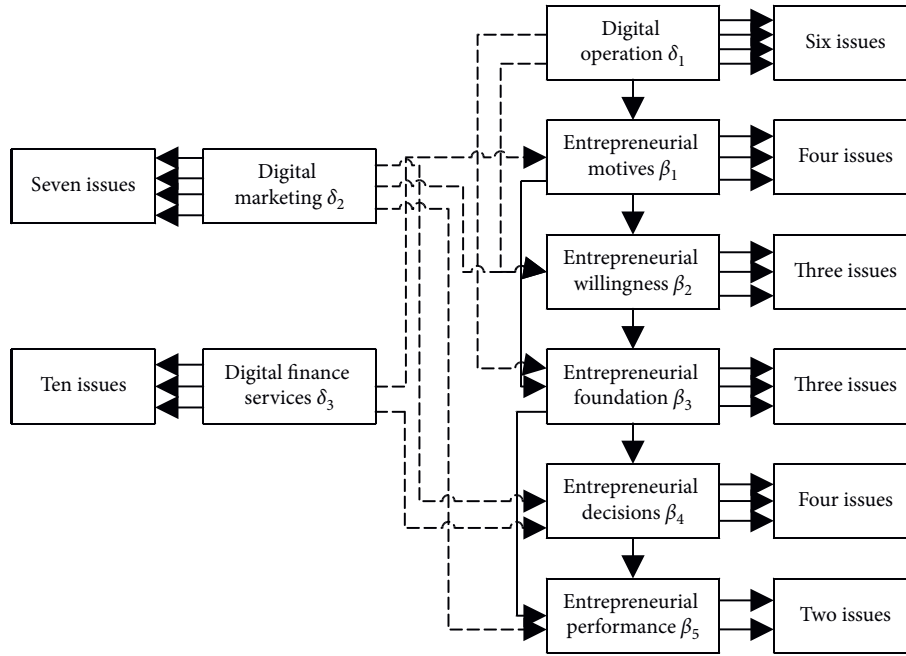
Figure 5: Paths of our evaluation model.

Table 1: Coefficient matrix $ZH(\gamma_i)$ of endogenous latent variables.

$ZH(\gamma_i)$					
0	0	0	0	0	0
0.3241	0	0	0	0	0
0.3624	0.4984	0	0	0	0
0.3102	0	0.0004	0	0	0
0.3110	0	0	0.7142	0	0
0.2631	0	0	0	0.3014	0

Table 2: Coefficient matrix $\Theta(\mu_i)$ of exogenous latent variables.

$\Theta(\mu_i)$					
0	0.4745	0.2120	0.2215	0	0
0.6412	0	0	0	0	0
0.3752	0	0	0	0	0
0.1789	0	0	0.1142	0.1842	0.1437
0.2648	0	0	0	0	0
0.4159	0	0	0	0	0

Table 3: Endogenous and exogenous latent variables under optimal IIVs.

δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7
51.1475	44.1562	52.8425	54.1251	52.2253	48.4252	45.6237
β_1	β_2	β_3	β_4	β_5	β_6	—
55.4013	56.5076	46.5625	62.2273	47.8468	49.1952	—

Table 4: Endogenous and exogenous latent variables under random IIVs.

δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7
58.035	47.2176	54.1037	51.3674	55.1623	49.3756	43.5408
β_1	β_2	β_3	β_4	β_5	β_6	—
54.3132	52.3208	48.7026	66.1258	46.3675	46.1952	—

TABLE 5: Cumulative variances of inputs and outputs in RMW entrepreneurship.

Variables	IIVs			Variance explained (ES)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	1.931	19.34	19.34	1.936	19.27	19.28
2	1.643	13.26	30.22	1.829	30.75	30.13
3	1.545	12.63	32.11	2.536	12.53	32.01
4	1.167	19.75	50.66	1.154	19.85	50.23
5	0.839	14.52	82.53	0.866	14.92	81.92
6	0.348	5.06	100.000			

TABLE 6: Cumulative variances of inputs and outputs in policy supports of digital finance.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	2.15	41.42	41.85	2.36	41.46	42.05	2.76	42.48	41.77
2	1.33	16.38	74.96	1.53	19.54	41.36	1.55	15.22	47.76
3	1.45	15.26	56.52	1.75	16.37	52.47	1.48	14.56	56.42
4	1.26	14.63	68.53	1.76	14.64	61.42	1.69	13.79	68.22
5	0.84	12.52	84.94	0.55	14.09	81.64	0.21	13.74	80.17
6	0.66	10.34	93.54						
7	0.51	6.34	100.00						

TABLE 7: Cumulative variances of inputs and outputs in third-party digital finance service providers.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	1.85	19.47	19.67	1.95	19.73	19.77	1.83	15.76	15.76
2	1.86	12.51	32.45	2.56	12.45	32.89	2.13	12.75	32.61
3	1.73	15.36	47.81	1.03	15.67	47.56	1.06	15.09	47.52
4	1.76	14.25	62.52	1.56	14.68	61.32	1.74	14.63	61.34
5	1.62	10.53	71.19	2.71	10.62	71.49	2.73	10.79	72.63
6	1.61	9.37	87.52	1.86	9.84	80.46	1.65	9.82	80.56
7	0.82	8.82	90.57						
8	0.76	6.25	96.16						
9	0.69	3.51	98.85						
10	0.27	1.02	100.00						

TABLE 8: Cumulative variances of RMW entrepreneurial community.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	2.24	51.36	51.76	2.56	51.35	51.35	1.86	45.72	45.72
2	1.03	25.72	75.98	1.27	25.71	76.97	0.95	24.52	70.65
3	0.36	18.26	95.07	0.74	18.43	95.42	0.96	24.31	95.27
4	0.85	4.51	100.00						

independent collection and docking of financial data, online-offline integrated service model, construction of mobile payment scenes, construction of rural big data platform, and risk control of financial digitization, greatly affect the state of latent variables. These core variables promote the entrepreneurial environment, entrepreneurial motives, and entrepreneurial performance.

Tables 8 and 9 show the cumulative variances of RMW entrepreneurial community and digital finance environment, respectively. It can be inferred that 95.07% of the information of RMW entrepreneurial community could be explained by three variables, and 85.62% of the information of digital finance environment could be explained by two variables. Comparing the paths between latent variables, five

TABLE 9: Cumulative variances of digital finance environment.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	2.45	61.08	61.08	2.45	61.08	61.08	1.89	43.71	43.71
2	0.76	24.12	85.62	0.76	24.65	85.67	1.55	39.73	85.69
3	0.12	3.45							

TABLE 10: Cumulative variances of macro environment of market economy.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	2.42	61.79	61.78	2.42	61.59	61.58	1.86	46.43	46.73
2	0.45	10.13	95.27	0.25	10.13	95.47	0.82	22.09	95.26
3	0.15	4.59	100.00						

TABLE 11: Cumulative variances of social service environment.

Variables	IIVs			Variance explained (ES)			Variance explained (RS)		
	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate	Total	Change rate	Cumulative change rate
1	1.82	44.23	44.53	1.72	44.23	44.23	1.64	41.36	41.12
2	1.19	29.34	84.17	0.62	16.73	90.95	0.93	24.53	90.82
3	0.62	16.75	90.84						
4	0.35	9.18	100.00						

core variables, namely, incubation model of entrepreneurial community, degree of coordination between upstream and downstream enterprises, completeness of entrepreneurial services, banking service, and insurance service, have large influences on the state of other latent variables.

Tables 10 and 11 show the cumulative variances of macro environment of market economy and social service environment, respectively. It can be inferred that 95.27% of the key information of macro environment of market economy could be explained by two variables. Four variables exert large influences of the state of subsequent latent variables, namely, industrial structure, per-capital consumption, contribution to regional economy, and contribution to regional employment. The changes of the four variables significantly influence the entrepreneurial environment, entrepreneurial motives, and entrepreneurial performance.

6. Conclusions

This paper mainly evaluates the influence of digital finance on the efficacy of RMW entrepreneurship. The first step is to build an influencing factor analysis model and an RMW entrepreneurship model and detail the principles for the structural equation modeling of the said influence. Next, the traditional PLS regression was optimized, the best IIVs were obtained, and the algorithm convergence was guaranteed. After that, a multilayer SEM was established to evaluate the said influence. Then, our improved algorithm was found to be more accurate than the traditional PLS regression

through comparative experiments, which estimate the latent variables and their coefficient relationships and derive the endogenous and exogenous latent variables under optimal and random IIVs. In addition, the cumulative variances of multiple factors (i.e., the inputs and outputs in RMW entrepreneurship, the inputs and outputs in policy supports of digital finance, the inputs and outputs in third-party digital finance service providers, RMW entrepreneurial community, digital finance environment, macro environment of market economy, and social service environment) were summarized to identify the core measured variables that greatly affect the latent variables.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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