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Evaluation of Financial Digitalization Maturity of Small and Medium-sized Enterprises Based on Fuzzy Logic Algorithm

Tong Tian*

KPMG Huazhen LLP Shenyang Branch, Shenyang 110000, China

In response to the problem of having inadequate and inaccurate methods of evaluating the digital maturity evaluation of small and medium-sized enterprises (SMEs), this study designed a financial digital maturity evaluation method based on the size of enterprises in a provincial region of China. By analyzing the current status of financial digitization in SMEs, evaluation indicators were determined, and a digital maturity evaluation model was constructed using fuzzy logic algorithms and analytic hierarchy process. Verification showed that the Cronbach's Alpha coefficient of the established evaluation model was 0.87, and the consistency ratio of the judgment matrix was 0.030. The average scores for digital management, input, output, and external digital environment of the 25 selected SMEs were 2.8008, 2.0588, 1.4964, and 1.7568, respectively. The average score for overall financial digital maturity was 1.6768, which is a relatively weak level. The results indicate that the financial digitalization maturity level of SMEs in the study area is relatively low. When undertaking digital transformation, it is necessary to strengthen the application of enterprise digital technology, optimize the digital business capabilities of enterprise finance, and promote the digital transformation of enterprise finance. The use of fuzzy logic algorithms to evaluate the digital maturity of enterprise finance can improve the efficiency and accuracy of evaluation and has positive practical significance in the field of evaluation.

Keywords: Fuzzy logic algorithm; AHP; SMEs; Digital transformation; Digital maturity; Evaluation model

1. INTRODUCTION

With the continuous advancement and innovation of information technology, Digital Transformation (DT) has become an inevitable trend for the development of global enterprises. For Small and Medium-sized Enterprises (SMEs), financial digitization not only improves the efficiency and transparency of financial management; it also provides more accurate data support for enterprise decision-making [1–3]. In today's rapidly developing digital age, SMEs, as an important source of social and economic vitality, have become a key means of strengthening enterprise competitiveness, optimizing resource allocation, and accelerating market response through their financial DT [4, 5]. However, the limitations of SMEs in terms of scale, resources, and capabilities have led to uneven maturity of enterprise financial digitization, and there is an urgent need for an effective evaluation tool to measure and guide the DT and development of enterprises. The Fuzzy Logic Algorithm (FLA), a mathematical tool for dealing with uncertainty and fuzziness problems, can effectively solve the quantitative problems that traditional evaluation methods face when assessing Financial Digital Maturity (FDM) [6, 7]. Therefore, this study conducts FDM assessment analysis on manufacturing SMEs in a provincial region of China to achieve accurate FDM assessment for SMEs and promote their financial DT. Through the Analytic Hierarchy Process

*E-mail of Corresponding Author: 18524497896@163.com

(AHP) and FLA, FDM assessment is applied to SMEs, and FLA is utilized to address any ambiguity and uncertainty in the evaluation indicators.

This paper is comprised of four parts. In Part 1, the research achievements and shortcomings of enterprise FDM assessment in the industry are examined. Part 2 researches and designs FDM assessment methods for SMEs based on FLA. Part 3 conducts experiments and analysis on the proposed SMEs-FDM assessment method. Part 4 summarizes the results and indicates future research directions.

2. RELATED WORKS

With the advancement of DT, an increasing number of enterprises have begun to realize the importance of financial digitization, and conducting research on enterprise DT has become a new direction for economists. Von Solms et al. proposed a Digital Maturity Evaluation (DME) method for the execution of the finance department in response to the increasing strategic importance and DT demands made of the bank's finance department after the 2008 financial crisis. By utilizing digital technology to analyze the digital maturity of the bank's finance department, the transformation to the next generation of "intelligent" digital finance departments was achieved while ensuring proper identification and prioritization of finance department activities and digital technology digitization [8]. In response to the shortcomings of existing DT maturity models in terms of suitability, completeness, clarity, and objectivity, Gökalp et al. proposed the development of a comprehensive DT maturity model. It helped organizations determine their current capabilities and maturity by applying theoretical foundations, and created an improved comprehensive roadmap in a standardized manner, thereby providing technical support for enterprise DT [9]. Wernicke et al. proposed the development of a DME framework for construction site operations, which includes evaluation domains, maturity levels, evaluation criteria, and evaluation procedures, to systematically evaluate and implement digital technologies to support improvements in this industry. It has been developed and validated through the use of literature and empirical data, thereby promoting long-term improvement of construction project portfolios [10]. Rao et al. proposed using the "Peking University Digital Finance Index" to determine the micro impact of financial innovation development on enterprise level environmental governance to address the research gap on the impact of digital finance on Enterprise Green Innovation (EGI). By considering endogeneity and the robustness of various indicators, it was found that digital finance has a significant positive impact on the quantity and quality of EGI in analyzing the capital flow mechanisms of different enterprises [11]. Lassnig et al. designed an online self-assessment method based on a data sample of 409 companies to clarify the digital readiness of the supply chain and the differences between SMEs and large enterprises. This study provided a theoretical reference for benchmarking and in-depth insights for companies by elucidating the DT gap between SMEs and large enterprises [12].

FLA, a mathematical processing method, has been widely applied in the field of evaluation. Maretto et al. developed a multi-criteria decision model built on FLA and AHP to address the implementation of the Industry 4.0 national plan and the increasingly fierce international competition that forces companies to carry out their industrial facility digitization projects. It combined the model with the hierarchical classification of existing digital technologies to highlight the benefits of adopting similar and easily interconnected technologies, achieving efficient decision-making for enterprise digital projects [13]. Kirmizi et al. proposed a general maturity model development framework based on design science research to improve the evaluation accuracy of DT maturity models. This framework utilized a concept-centered table approach to obtain classification schemes, solving the granularity extraction problem of research roadmap and design features [14]. To ensure that network enterprises select suitable DT business models under multiple factor evaluation conditions, Telnov et al. proposed a methodology based on the St. Gallen framework. The researchers' knowledge system based on fuzzy production rule sets provided decision support for network enterprises, enabling them to make reasonable choices of business models in obtaining multi-criteria evaluations of network effects, digital maturity, and ensuring economic and information security [15]. Leso et al. developed a conceptual framework grounded on dynamic capability theory and digital maturity perspective to enhance the capabilities of mature organizations. It used flexible pattern matching methods to compare with four case studies of mature digital organizations, solving the DT transformation problem of different enterprise organizations in the digital business ecosystem [16].

Based on the above, economists have conducted extensive research on DT and achieved good results. However, the current research methods are specifically targeted, lacking universality and applicability, and are not suitable for the DT strategy of Chinese SMEs. In addition, most existing studies have overlooked the issue of weighting standards or dimensions in the DT maturity evaluation process. Therefore, this study proposes a DT evaluation system suitable for SMEs based on FLA to improve the FDM assessment efficiency of SMEs. Its novelty lies in the construction of four evaluation indicators for SMEs' financial digitization, and empirical analysis based on the maturity of financial digitization of manufacturing SMEs.

3. METHODS AND MATERIALS

Firstly, an analysis was conducted to determine the current status of financial digitalization development of SMEs in the manufacturing industry in a provincial-level region of China. By formulating principles and criteria for DME, evaluation indicators were determined, and SMEs-FDM assessment system was established. AHP and FLA were used to evaluate the FDM of SMEs. The weights of evaluation indicators were determined by using AHP, and then FLA was conducted to determine the evaluation results of the evaluation model.

3.1 Construction of SMEs-FDM Assessment System

To improve the FDM assessment efficiency of SMEs, this study first analyzes the key factors of the FDM composition

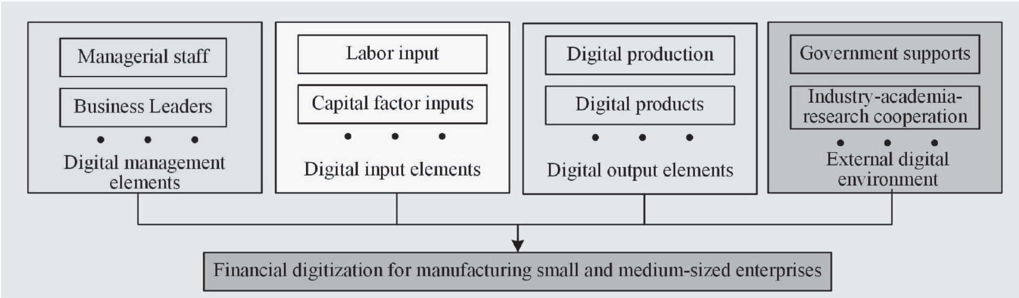


Figure 1 FDM components for manufacturing SMEs.

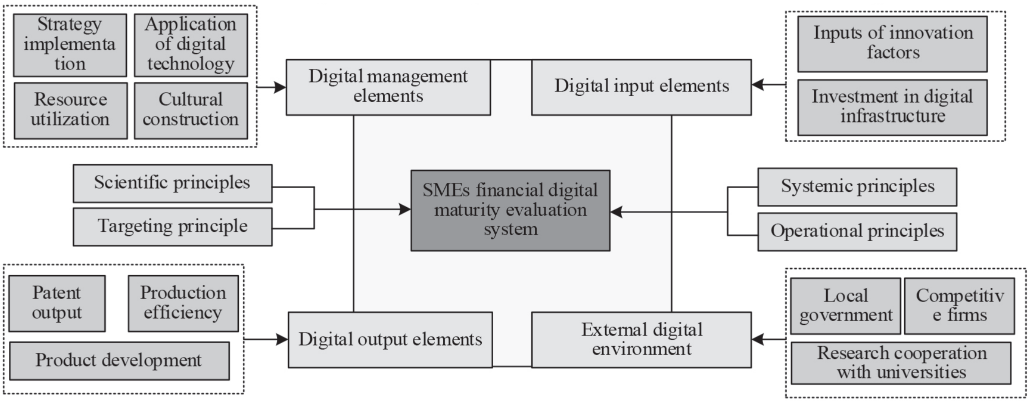


Figure 2 Principles and selection basis for the establishment of FDM assessment index system.

of SMEs in the manufacturing industry. These SMEs have limited financial resources, risk management capabilities, and bargaining power with technology suppliers, which places high demands on the capabilities of enterprise managers. Therefore, the success of financial digitization adoption by manufacturing SMEs will be constrained by the management team. The input of labor and capital factors will also affect the development of SMEs. The output capability of enterprise digital products determines the digital maturity level of the company. Based on the above, this study suggests that the FDM components of manufacturing SMEs can be shown in Figure 1.

As shown in Figure 1, the FDM components of manufacturing SMEs are: management, input, output, and external environment. The management elements determine the complementary ability of enterprise resources and promote the construction of a digital culture in SMEs. The input factors are the labor input and the capital input. The DT of manufacturing SMEs is a constantly evolving process that requires a concentrated demand for resources and continuous investment of funds and manpower to maintain their efficient operation. The arrival of Industry 4.0 has increased demands for SMEs' digital investment. The output factors are the SMEs' digital products and production, which have a positive impact on SMEs' DT. The external environment is an important factor that influences the survival and development of enterprises, and the development of the external digital environment is the main driving factor enabling SMEs to achieve DT. Based on the constituent elements of digital maturity, this study further establishes the principles and selection criteria for the evaluation system. The specific indicators are shown in Figure 2.

In Figure 2, the design of the proposed evaluation system follows the principles of science, systematicity, focus, and practicality. Scientificity refers to the establishment of the entire system on the basis of relevant scientific theories. Systematicity refers to the comprehensive and systematic evaluation indicators of the proposed system, covering the essence of SMEs' digital maturity. Focusing refers to fully considering the actual situation of the research object and selecting indicators that fully map the digital maturity of the research object. Practicality refers to the ease of selecting theoretical and appropriate indicators. Table 1 shows the selected SMEs-FDM assessment indicators.

As shown in Table 1, the proposed DME system consists of primary and secondary indicators. The first level indicators comprise four elements: digital management, input, output, and external digital environment. The elements of digital management correspond to four secondary indicators: digital implementation, digital technology use, resource utilization and development, and cultural construction. The main elements of digital investment are: infrastructure, information technology, highly-educated talents, and investment in research and development capital. The factors of digital output are: the production efficiency and innovation of patents and products. The external environment comprises: government policies, competitive enterprises, and university cooperation.

3.2 SMEs-FDM Assessment Model Based on FLA

Based on the proposed DME system, this study utilizes AHP and FLA for SMEs-FDM evaluation. Firstly, it

Table 1 SMEs-FDM assessment system.

First-stage indicator	Secondary indicators
Digital stewardship capability	Degree of implementation of digital strategy
	Degree of digital technology application
	Degree of digital resource utilization
	Degree of digital culture construction
Digital input capability	Proportion of digital infrastructure investment
	Proportion of information technology investment
	Proportion of digital knowledge talent investment
	Proportion of digital research and development capital investment
Digital output capability	Efficiency of digital patent output
	Success rate of digital product development
	Efficiency of digital production
	Innovation degree of digital products and services
External digital environment	Local government support strength
	Degree of digitalization of competing enterprises
	Degree of cooperation between industry, universities and research institutions

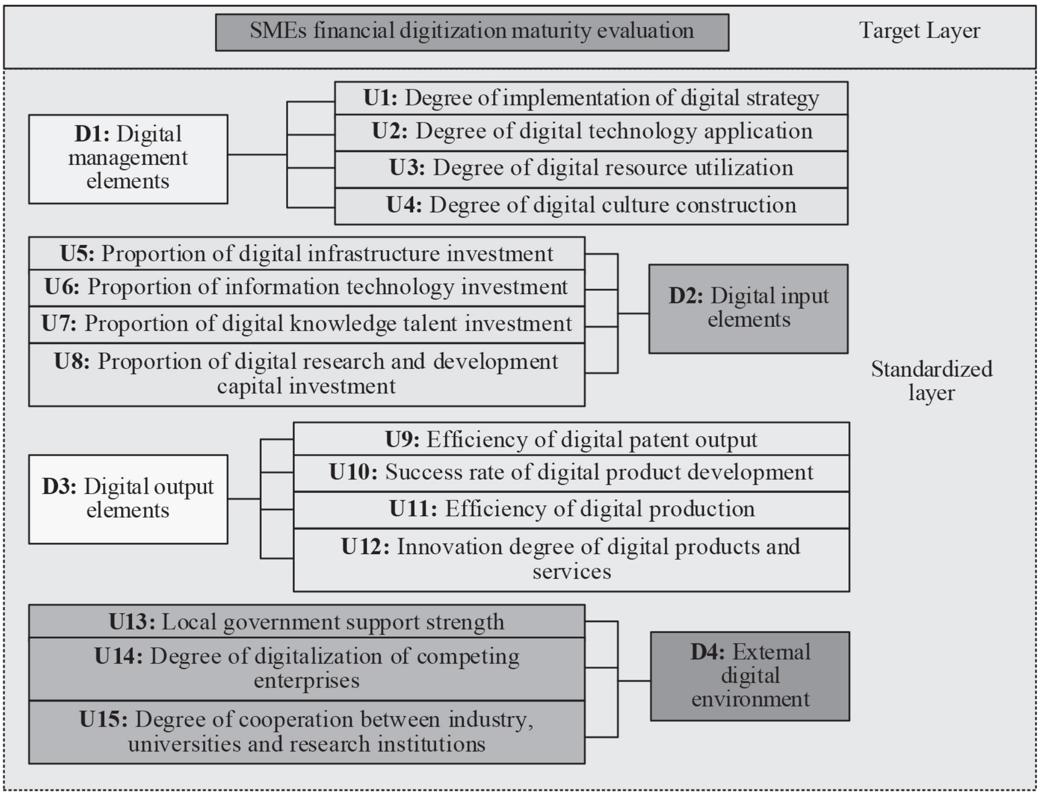


Figure 3 AHP-based hierarchical modeling.

uses AHP to ascertain the hierarchical relationship between each constituent element and determine the weight of each indicator. Secondly, FLA is used to obtain the results of the evaluation of the SMEs' level of development of financial digitization. The hierarchical structure of the evaluation model's system indicators determined by AHP is shown in Figure 3.

In Figure 3, AHP divides the SMEs-FDM assessment system into two levels, mainly including the objective layer and the criterion layer. Among them, the criterion layer includes sub criterion layers. According to the division of criterion layer and sub-criterion layer, AHP calculates the hierarchical relationship and weight of constituent elements. For the four criterion layers C1, C2, C3, and C4, the comparison formula of their judgment matrices can be shown in Equation (1) [17, 18].

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ \frac{1}{a_{12}} & 1 & a_{23} & a_{24} \\ \frac{1}{a_{13}} & \frac{1}{a_{23}} & 1 & a_{34} \\ \frac{1}{a_{14}} & \frac{1}{a_{24}} & \frac{1}{a_{34}} & 1 \end{bmatrix} \tag{1}$$

In Equation (1), A is the judgment matrix. a is the importance of one criterion relative to another criterion. According to the judgment matrix, the weight vectors of each criterion are further calculated, and the specific formula is Equation (2) [19].

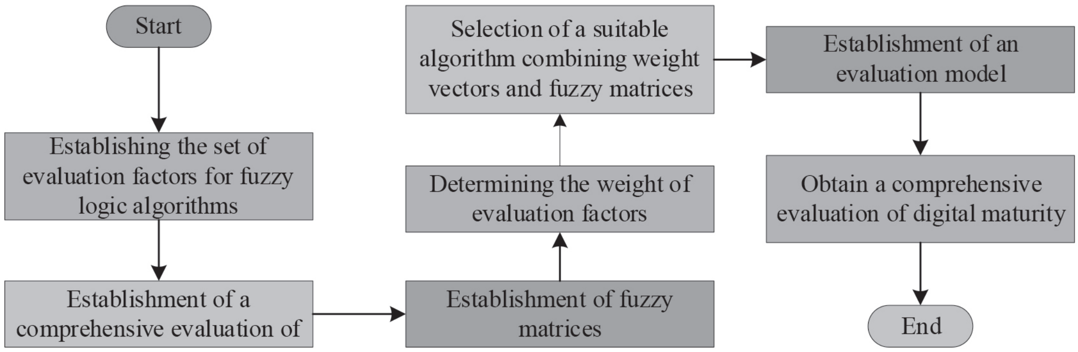


Figure 4 Calculation process of evaluation model constructed by combining AHP and FLA.

$$\begin{cases} W = \{w_1, w_2, w_3, w_4\} \\ Aw = \lambda_{max} w \end{cases} \tag{2}$$

In Equation (2), W is the weight vector of four criteria. w_1 is the weight of digital management capability. w_2 is the weight of digital investment capability. w_3 is the weight of digital output capability. w_4 is the weight of the external digital environment. λ_{max} is the maximum eigenvalue of the judgment matrix. After conducting consistency checks on the AHP judgment matrix, it is combined with FLA to further construct the SMEs-FDM assessment model. The consistency check expression is Equation (3) [20, 21].

$$\begin{cases} CI = \frac{\lambda_{\max} - n}{n-1} \\ CR = \frac{CI}{RI} \end{cases} \tag{3}$$

In Equation (3), CI is the consistency indicator. n is the order of the judgment matrix. CR is the consistency ratio. RI is the random consistency index, which depends on the end of the judgment matrix. The specific calculation of the proposed SMEs-FDM assessment model is shown in Figure 4.

In Figure 4, the model first establishes a set of comprehensive evaluation factors and evaluation results, and establishes the membership degree of the evaluation object corresponding to the evaluation set, thereby establishing a fuzzy matrix. Secondly, it uses AHP to decide the weight coefficients of evaluation factors and constructs a weight set. Then, according to the synthesis operator, the weight set is combined with the fuzzy matrix to obtain the result vector of fuzzy evaluation. Finally, based on the weighted average principle, the result vector is processed and the comprehensive evaluation score of the evaluated object is obtained. The expressions for the evaluation factor set and the comment set are shown in Equation (4).

$$\begin{cases} B = \{b_1, b_2, \ldots b_m\} \\ D = \{d_1, d_2, \ldots d_v\} \end{cases} \tag{4}$$

In Equation (4), B is the set of evaluation factors. b is the influencing factor of the evaluation object. m is the number of influencing factors. D is a collection of comments. d is the evaluation result. v is the number of evaluation results. The fuzzy matrix formula is Equation (5).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1v} \\ r_{21} & r_{22} & \cdots & r_{2v} \\ \ldots & \ldots & \ddots & \ldots \\ r_{m1} & r_{m2} & \cdots & r_{mv} \end{bmatrix} \tag{5}$$

In Equation (5), R is a fuzzy matrix. r_{mv} is the membership degree of evaluation result d_v in comment set D. The synthesis operator combines the fuzzy matrix and the set of weights to obtain the fuzzy evaluation result matrix as shown in Equation (6).

$$U = W \times R \tag{6}$$

In Equation (6), U is the matrix of fuzzy evaluation results. The overall evaluation score of the object is calculated with Equation (7).

$$Y = \frac{\sum_{j=1}^{v} f_j^2 \cdot j}{\sum_{j=1}^{v} f_j^2} \tag{7}$$

In Equation (7), Y is the final score of the evaluated object. f_j is the score for the j-th evaluation level.

4. RESULTS

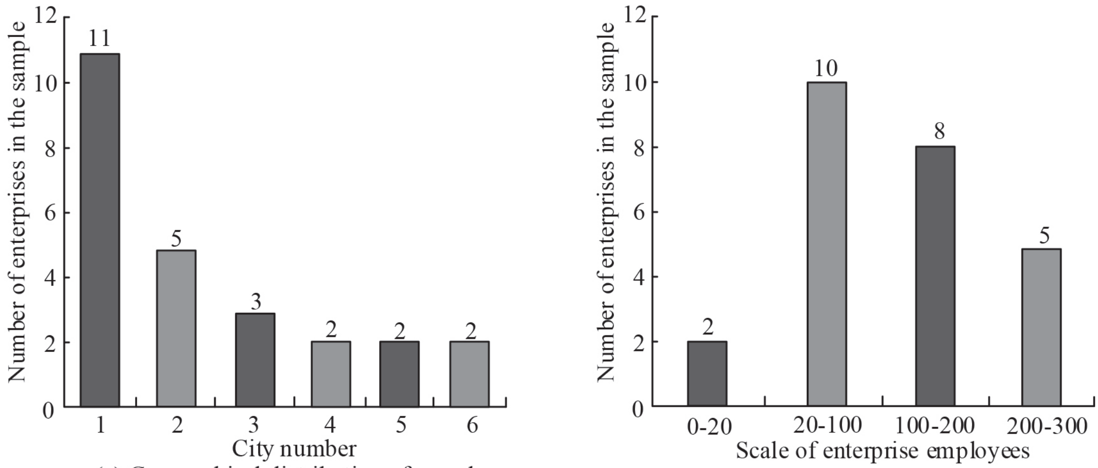
This study first validated the performance of the proposed evaluation model combining AHP and FLA, and conducted feature analysis on the obtained data samples. Secondly, a case evaluation and verification were conducted based on the financial DT data of SMEs within the manufacturing industry in a certain province of China.

4.1 Testing of Evaluation odels, and Analysis of Sample Characteristics

To ensure the effectiveness of the research model, the performance of the model was first validated and analyzed. 25 SMEs manufacturing enterprises in a provincial region of China were selected as data samples, and a questionnaire survey method was used to collect information as evaluation data for SMEs-FDM. The survey questionnaire contained items seeking respondents' demographic information, and questions related to the level of digitalization adopted for the SMEs' finances. A Likert-type scale was used to determine the level of digital maturity of the enterprise; the higher the score, the higher the level of digital maturity. The entire

Table 2 CAC validation results.

Dimension	Number of entries	Cronbach's Alpha after deletion of terms	Cronbach's Alpha
Digital management capability	4	0.78	0.85
		0.83	
		0.79	
		0.80	
Digital input capability	4	0.75	0.83
		0.78	
		0.80	
		0.79	
Digital output capability	4	0.76	0.84
		0.78	
		0.79	
		0.78	
External digital environment	3	0.78	0.87
		0.82	
		0.80	
Summary	15	/	0.87



(a) Geographical distribution of sample enterprises

(b) Characteristics of employee size in sample enterprises

Figure 5 Geographical distribution and staff size of sample firms.

survey period was from July 2023 to August 2023, with 400 questionnaires collected and 350 valid questionnaires being suitable for analysis. The analysis software SPSS 25.0 was used to perform statistical analysis on the obtained data. Table 2 shows the test results for the reliability of the scale.

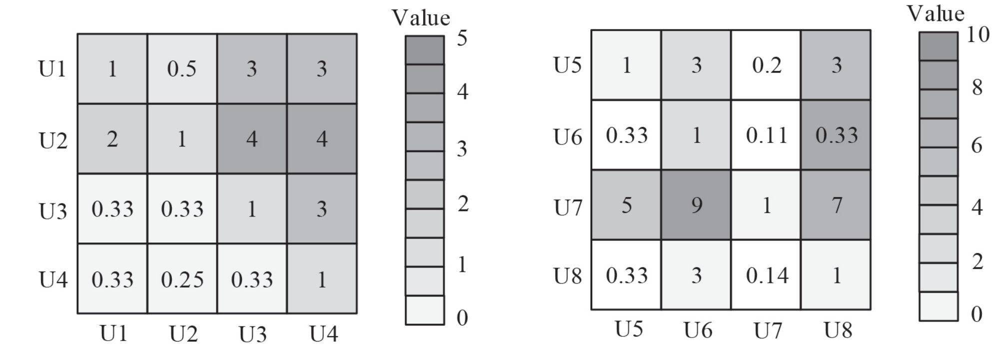
Table 2 shows the test results of Cronbach's Alpha Coefficients (CAC). CAC evaluates the reliability of the entire scale by analyzing the consistency of questionnaire items. The closer its value is to 1, the better the internal consistency of the scale, that is, each item measures a common latent variable. In Table 1, the value of the variables in the entire scale is 0.87 and, after removing the question items, the CAC is smaller than the initial CAC, indicating that all question items can be retained, confirming the reliability of the scale. On this basis, this study analyzes the characteristics of the selected SMEs. The research object is located in Western China, which has six prefecture level cities within its region. Figure 5 shows the geographic distribution of 25 manufacturing SMEs and the number of employees in these enterprises.

Figure 5 (a) shows the distribution of selected enterprises within the study area. Among them, prefecture level cities are ranked 1–6 based on their economic development status. The more developed the economy, the more SMEs are distributed in cities. In the demographic information of personnel in the 25 enterprises shown in Figure 5 (b), the number of employees in the selected enterprises meets the requirements of SMEs-FDM assessment. The demographic information of the surveyed individuals is presented in Table 3.

In Table 3, the surveyed personnel of the selected companies are mostly undergraduates, with 28.6% of them being financial personnel. The proportion of personnel in other job positions, including management, technical, marketing, production, and others, is 8.3%, 7.1%, 23.0%, 17.0%, and 16.0%, respectively. Overall, the surveyed personnel were diverse in terms of demographic characteristics, thereby strengthening the validity of the questionnaire survey data and ensuring accurate evaluation of SMEs-FDM.

Table 3 Characteristics of respondents in selected enterprises.

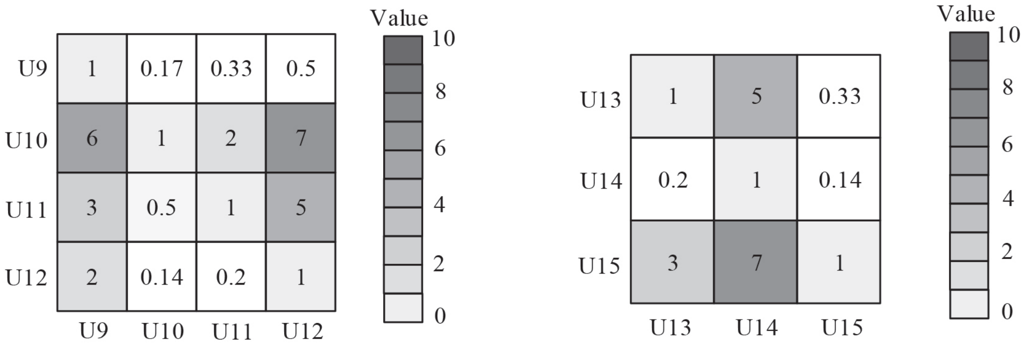
Variant	Variable content	Proportions (%)	Variant	Variable content	Proportions (%)
Gender	Male	53.0	Position	Management	8.3
	Female	47.0		Financial	28.6
Education	Junior College and below	33.6		Technical	7.1
	Bachelor	47.3		Marketing	23.0
	Master	15.1		Production	17.0
	Doctorate	4.0		Others	16.0



(a) Small and medium-sized enterprises financial digital management capability judgment matrix

(b) Small and medium-sized enterprises financial digitization input capacity judgment matrix

Figure 6 Judgment matrix of SMEs financial digital management capacity and input capacity.



(a) Judgment matrix for SMEs' ability to digitize financial outputs

(b) Externally digitized judgment matrix

Figure 7 Judgment matrix of digital output capacity and external digital environment.

4.2 Empirical Analysis of Evaluation

Based on the FDM questionnaire survey results obtained from 25 companies, this study first conducts consistency testing. Figure 6 shows the judgment matrix of digital management capability and investment capability factors.

Figure 6 (a) shows the sub criterion layer judgment matrix of digital management capability. According to the judgment matrix, the consistency ratio of digital management capability is 0.066, and the maximum eigenvalue is 4.175. According to Figure 6 (b), the maximum eigenvalue of the judgment matrix for the four sub criteria layers of digital investment capability is 4.176, with a consistency ratio of 0.066. Figure 7 shows the judgment matrix of digital output capability and external digital environment.

Combining the judgment matrices outside of Figure 7 (a) and (b), the maximum eigenvalues of the matrices for both are 4.147 and 3.065, respectively, where the consistency ratio of digital output capability is 0.055, and the consistency ratio of external digital environment is 0.062. Combining the judgment matrices of four criterion layers, this study determined that the consistency ratio of the judgment matrix of the DME model is 0.030. The consistency ratio of all judgment matrices is less than 0.1, indicating that after pairwise comparison, the results obtained by experts and research are consistent and there is no logical contradiction. At the same time, this further confirms that the variable weights calculated by AHP are reliable. Figure 8 shows the weights of various indicators of digital maturity calculated by AHP.

In Figure 8 (a), the weight of the digital management capability indicator is 0.282. The degree of implementation of digital strategy (U1) has a single weight of 0.293 and a comprehensive weight of 0.083. The individual weight of the degree of digital technology application (U2) is 0.476,

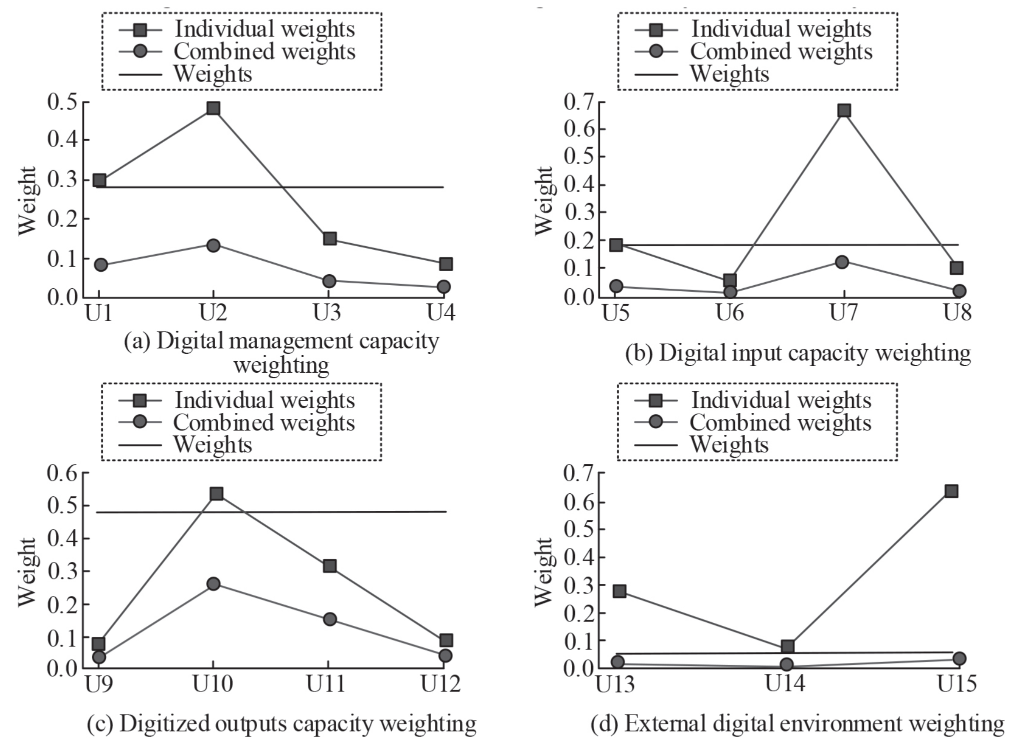


Figure 8 SMEs-FDM assessment indicator weight.

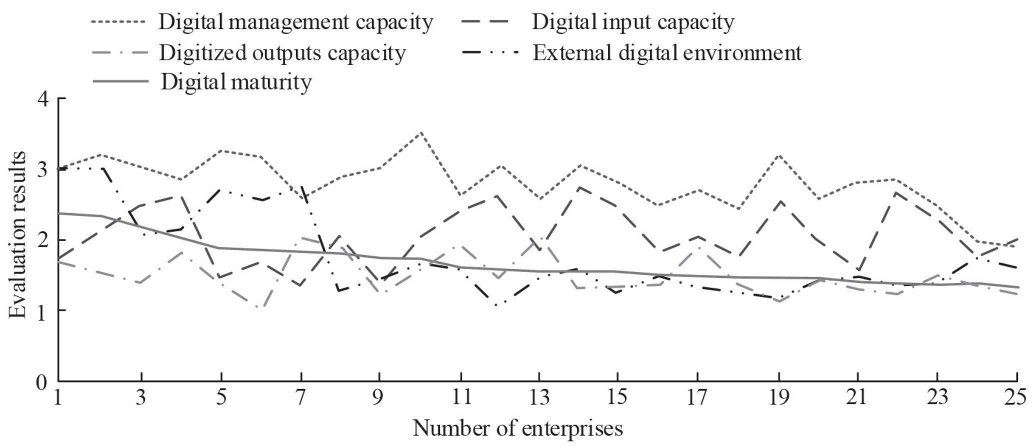


Figure 9 Composite score for FDM of the selected 25 companies.

and the overall weight is 0.134. The individual weight and comprehensive weight of the degree of utilization of digital resources (U3) are 0.147 and 0.042, respectively. The individual and comprehensive weights of the degree of digital cultural construction (U4) are 0.0834 and 0.023. The degree to which enterprises adopt and apply digital technology has the greatest impact on digital management capabilities, and it has a higher weight value. In Figure 8 (b), the weight of digital investment capability is 0.183. The individual weight and overall weight of the amount of investment in highly-educated talent (U6) are the highest among the four sub criteria layers, at 0.662 and 0.121, respectively. This indicates that investment in talent has a strong impact on the digital maturity of enterprises. Educational talents are an important means whereby SMEs can carry out digital technology innovation. The use of highly educated employees for research and development purposes is conducive to the efficient and scientific development of digital technology. According to Figure 8 (c) and (d), the weights of digital output capability (U7) and external digital environment (U8) are 0.482 and 0.053, respectively. Of the two indicators, the corresponding secondary indicators' probability of "successful digital product development (U10)" and "strength of industry university research cooperation (U15)" have the highest individual and comprehensive weights. This indicates that the two secondary indicators have a significant impact on their respective primary indicators. The higher the probability of successful research and development of digital products, the greater the market share of SMEs in the digital product market, and enterprises will obtain more digital benefits. Universities and research institutions can provide support for the digital development of SMEs, thereby promoting their digital technology innovation. Based on the determined weights of each indicator, this study conducted FDM assessments on 25 enterprises, as shown in Figure 9.

In Figure 9, the digital maturity scores for the finances of the 25 SMEs' are mostly between 1–2 and 2–3 points. According to a 5-point scale, the evaluation is equivalent, with ratings mostly being weak and average. Among them, there are 4 enterprises with FDM scores above 2, accounting for 16% of all enterprises, and the highest score is only 2.37. This indicates that the development of SMEs-FDM in the provincial region is relatively low, basically being at a weak or moderate level. Among the four evaluation indicators, the digital output capability of the 25 enterprises in the study area is the worst. This indicates that SMEs in the region place less emphasis on digital output and the need to improve their financial digital output capabilities in order to enhance the digital maturity of the region. The evaluation score for digital management capability is the highest, with 36% of all enterprises scoring above 3 points, and only 8% of enterprises scoring below 2 points. This indicates that SME leaders attach great importance to the development of enterprise digitization and have superior digital management capabilities. Overall, the scores of the four indicators of financial digitization for the 25 enterprises are rated as average. This indicates that the financial digitalization maturity of enterprises within the provincial region is relatively low and their development is weak. Multiple measures are needed to improve the level of digitalization maturity.

5. CONCLUSION

To improve the accuracy of enterprise DME, this study proposed a SMEs-FDM assessment method based on FLA. Based on 25 SMEs in a provincial region of China, a DME system was constructed using digital governance efficiency, investment efficiency, production efficiency, and external environment as indicators. Meanwhile, AHP and FLA were utilized to establish SMEs-FDM assessment models. Empirical evidence showed that the CAC of the research model was 0.87, and the CAC after removing the term was smaller than the initial CAC. The average score for the digital management capability of 25 enterprises was 2.8008, the average score for the digital input capability was 2.0588, the average score for the digital output capability was 1.4964, and the average score for the external digital environment was 1.7568. The average score of SMEs-FDM in the research area was 1.6768. The data showed that the evaluation results of the proposed DME model were consistent with expert ratings, and the evaluation of SMEs-FDM was accurate and effective. The level of SMEs-FDM in the manufacturing industry within the research area was relatively weak, and there was a need to further strengthen and improve the digital output factors to enhance the level of digital maturity. However, the selection of AHP and FLA is subjective and, in future work, more objective methods will be adopted to optimize them, improve the DME system, and promote enterprise DT.

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